Giver and the Receiver: Understanding Spillover Effects and Predictive Power in Cross-market Bitcoin Prices

Marc Gillaizeau[1]*, Ranadeva Jayasekera[2], Ahmad Maaitah[3], Tapas Mishra[3], Mamata Parhi[4], Evgeniia Volokitina[5]

[1] Centre for Evaluation and Development (C4ED), Germany
[2] Trinity College Dublin, Ireland
[3] University of Southampton, UK
[4] University of Roehampon, UK
[5] ITMO University, Saint Petersburg, Russia

Abstract

We identify and characterise the 'givers and the receivers' of volatility in cross-market Bitcoin prices and discuss international diversification strategies in this context. Using both time and frequency domain mechanisms, we provide estimates of outward and inward spillover effects. These have implications for (weak-form) cross-market inefficiency. In our setting, we treat high-degree of spillover as an indicator of weak-form inefficiency because investors can utilise information on the dynamic spillover effects to produce a best long-run prediction of the market. Our results show that Bitcoin prices depict strong (dynamic) spillover in volatility, especially during episodes of high uncertainty. The Bitcoin-USD exchange rate possesses net predictive power, mirrored by the tendency of the Bitcoin-EURO market as a net receiver relative to other markets. Robustness exercise generally supports our claim. The overall implication is that during episodes of high uncertainty, Bitcoin markets depict greater dynamic inefficiency, instrumenting the role of asymmetric information in the path-dependence and predictive power of Bitcoin prices in an interdependent market.

Keywords: Cross-market Bitcoin prices; Return and volatility spillovers; Uncertainty; Inefficiency; Prediction

JEL Classification: C1; E4; D5

*Gillaizeau (E-mail: gillaizeau@c4ed.org); Jayasekera (E-mail: jayasekr@tcd.ie); Maaitah (E-mail: Ahmad.Maaitah@soton.ac.uk); Mishra (E-mail: t.k.mishra@soton.ac.uk); Parhi (E-mail: mamata.parhi@roehampton.ac.uk); Volokitina (E-mail: evolokitina@first-privacy.com).

Acknowledgement: We sincerely thank two anonymous referees and the editor, Prof. Brian Lucey for many helpful comments. We also thank Raju Chinthalapati, Athanasios Sakkas, Larisa Yarovaya and Eng-Tuc Jeremy Cheah for comments on an earlier version of the paper. Usual disclaimer applies.

1 Introduction

Since it was actively traded in 2013, Bitcoin – the biggest and most active cryptocurrency with a market capitalization over $110[1] billion – has struck investors' expectations of a quick and sizeable return, like none other. In the absence of strict monetary and financial regulations, cryptocurrency investors seem to be fully exploiting this opportunity and are quickly moving from a state of despondency (due to recurrent losses from their investments in regulated financial markets) to one of hope (because, Bitcoin prices are fundamentally driven by the 'feeling and the memory' of investors at a point of time.[2] To investigate the nature of such type of investment decisions and help governments design adequate regulations for limiting cross-market movement of shocks, a remarkable growth of research has sprung lately.

A helicopter survey[3] reveals that the literature has focused on two main aspects of cryptocurrency price movements. First, conceptual designs aiming to depict potential weaknesses of this market show how the latter can subject investors to insurmountable unsystematic risks (see for instance, Cheah & Fry, 2015; Cheah et al., 2018; Gandal et al., 2018). Second, a plethora of empirical research has systematically presented state-of-the-art estimation techniques to identify, among others, informational inefficiency (viz. Urquhart, 2016), long-range persistence behavior and cointegration (viz. Alvarez-Ramirez et al., 2018; Caporale et al., 2018; Cheah et al., 2018), volatility spillovers and dynamic interactions with other financial assets (viz. Corbet, Meegan, et al., 2018). Thus far, the extant research has laregely focused on a cross-section of cryptocurrencies and sparsely on a cross-market dynamics of a single cryptocurrency (except for the leading work of Cheah et al., 2018). The current paper aims to contribute to this nascent literature by studying volatility spillover across Bitcoin markets, exchanged in various currencies.

The issue of cross-market volatility has been studied in a macroeconomic context (for instance, Diebold & Yilmaz, 2012), where it is shown that volatility spillover is more profound when market interdependence is high, especially during financial crisis and episodes of economy-wide uncertainty (Cheah et al., 2018). Information on a *within-market* transmission of shocks possesses high policy value because viable policy interventions can limit possible proliferation of shocks beyond certain acceptable bounds. Moreover, managing

[1]coinmarketcap.com (Oct 2018)

[2]See Cheah et al. (2018) for details.

[3]Theoretical and empirical research in cryptocurrencies can be broadly divided into three important interdependent areas; viz., regulations and information system research, financial market and monetary theoretical formulation of cryptocurrency demand/supply, and development (and applications) of state-of-the-art econometric and/or statistical mechanics to understand (predictive patterns of) price movements. To minimize space and repetition of a succinct literature review, interested readers are encouraged to refer to Corbet, Lucey, et al. (2018) for an excellent survey.

shocks *within* a system is relatively easier as one can exploit the *system dynamic* features of shocks so as to monitor their movements and generate better predictive power for an asset. Although Bitcoin is traded electronically, like a huge number of assets globally, cross-economy differentials in the trading of Bitcoin reflects not only the role of macroeconomic and financial market regulations, but also represent investors' sentiment concerning an investment in a risky asset. While former studies (such as Corbet, Meegan, et al. (2018)) shed light on spillover effects of volatility from a 'cryptocurrency market' to 'other asset markets' (such as stock and gold), Cheah et al. (2018) demonstrated the importance of cross-market dynamic interdependence of Bitcoin prices by estimating a system-wide long-memory. The focus on a cross-market rather than a single market cryptocurrency market in the latter study holds significance in our context: by modelling directional spillover effects one creates a stock of information for investors who decide on an arbitrage value of Bitcoin traded in various markets. The investors exploit information on the predictive power of each market, such as the net receiver and net giver of volatility. Such a study is helpful in shaping robust investment strategy of a single cryptocurrency traded in various markets.

Broadly speaking, the current paper's main aim is to improve our limited understanding of the *cross-market* spillovers of volatility in Bitcoin prices and the predictive power each market possesses relative to others. Since Gandal et al. (2018) showed that Bitcoin prices can be seriously manipulated, a thorough understanding of volatility movements across Bitcoin markets is important to gauge net predictive power of each market. Accordingly, this paper contributes to the literature in two significant ways. First, differing from the convention, we study *spillover effects of return and volatility across markets* for a single cryptocurrency. Although study of spillover effects between a cryptocurrency market and a conventional asset market offers important insights on if and whether shocks from cryptocurrency market impact volatility in an asset market, it lacks in a directional predictive power. This is because these two markets are distinct with respect to the modes of operandi. Moreover, to the best of our knowledge there is no available financial theoretic model to justify conditioning predictive power of an asset market on the volatility in a cryptocurrency market. In this light, a major contribution of the current paper is to quantify (dynamic) spillover effects in cross-market Bitcoin prices. By doing so, we aim to shed light on the net receiver and prime giver of volatility across markets. As a further contribution, we employ Parkinson's (1980) high-low volatility measure as well as Garman-Klass type of volatility estimates to capture dynamic movements between high and low Bitcoin. Using these volatility measure (details of which will be presented in Section 2), we show that the Bitcoin-USD exchange rate possesses net predictive power and that the Bitcoin-EURO market appears to be a net receiver of volatility relative to other markets. Eventually, such tendencies could help investors design trending strategies to systematically beat the market.

To investigate further, the rest of the paper is planned as follows. Section 2 discusses data and summary statistics. section 3 discusses estimation method. Section 4 presents empirical results and robustness analyses. Section 5 concludes and presents the main implications of our research.

2 Data and summary statistics

Bitcoins are traded in a number of currencies in a number of exchanges across different countries. For the purpose of our analysis, we limit our sample to 5 Bitcoin/currency pairs with less than 26 percent missing values over the sample period . That is, the U.S. dollar (USD), Australian dollar (AUD), Canadian dollar (CAD), euro (EUR), and British pound (GBP). Although Bitcoins in USD, AUD, CAD, and EUR have started trading before December 1, 2011, Bitcoins in GBP started trading from January 1, 2012. For Bitcoin in CAD and EUR there are some missing closing prices during the early years in the sample period. Thus, the availability of the daily closing prices varies across different currencies.[4] Moreover, to lend comparison to the empirical results of Cheah et al. (2018) who investigate cross-market long-memory interdependency in Bitcoin prices, we limit our observation period span to March 12th 2013 to January 31st 2018. We collect data from the aggregation website Bitcoin Charts (www.bitcoincharts.com). Data prior to 25/2/2014 are collected from Mt.Gox. Subsequent to Mt. Gox closure the remaining observations were collected from other exchange platforms such as Bitstamp (the largest European Bitcoin exchange) and LocalBitcoins.[5]

Daily continuously compounded returns are computed by taking the first difference of log-transformed close price series. Our chosen measure of volatility is Parkinson's High-Low historical volatility (HL-HV) model.[6] The reasons for choosing this approach are twofold. First, the HL-HV model deals with sensitivity to trading hours more efficiently than the more intuitive close-to-close volatility model (Bennett & Gil, 2012). Second, this model generates more significant information and improves the efficiency of the volatility estimate (Parkinson, 1980). Consequently, Bennett and Gil (2012) claim that Parkinson's volatility measure is more efficient and productive than popular close-to-close volatility estimates.

Formally, V for each of our five Bitcoin to currency exchange rates is calculated as follows.

[4]Initially, we gained price data in various currencies after considering the length of observation, the frequency of non-trading date as well as trading volume. The five exchange markets considered in our work still cover more than 80% of market trading, which can fairly represent the whole market.

[5]At the time of undertaking estimation of the paper, we gathered data from various sources so as to allow us to construct a continuous time series data. It's possible that different websites report slightly different prices. Our estimation showed no significant differences in the estimates. Results are available with the authors.

[6]Following an anonymous referee's suggestions, an alternative measure of volatility, viz., Garman-Klass measure - has been used for robustness exercise. The results are discussed in Section 4.3.2.

$$V = 100 \times \left(\frac{1}{4\ln(2)} . \ln\left(\frac{h}{l}\right)^2 \right) \quad (1)$$

where h and l are the highest and lowest exchange rates on a given trading day, respectively. The estimator above computes the daily variance, hence, the corresponding estimate of the annualised daily percent standard deviation (volatility) is computed as follows:
$Vol = \sqrt{365 * V}$

Given their temporal dimension, all return and volatility series are checked for stationarity with the help of Augmented Dicky Fuller (ADF) and Philips-Perron (pperron) unit root tests (Dickey & Fuller, 1979; Phillips & Perron, 1988). Results are presented in Tables A.1 and A.2 (for returns and volatility, respectively) in the online appendix. Both tests suggest to systematically reject the null of the presence of a unit root with 99% confidence for every daily returns series (Table A.1), suggesting the latter are stationary. Similarly, the null is rejected at the 1% threshold for all tests carried out on exchange rate volatility series (Table A.2), and we conclude that our volatility series are also stable.

Table 1 provides summary statistics of the individual daily returns series (upper panel) and volatility (lower panel). The returns series are plotted in Figure 1. Average daily returns are similar across individual series and range from about 0.3 (BTC/USD, BTC/EUR and BTC/GBP) to around 0.34 (BTC/AUD). Median daily returns are systematically lower than average ones, hinting at potentially asymmetrically distributed series. Indeed, Bitcoin to USD (BTC/USD) and Bitcoin to GBP (BTC/GBP) exchange rates returns exhibit a small negative skew, suggesting a slightly larger concentration of observations to the right of their central tendency, while all other series are characterised by a positive third statistical moment (long right tails), although it is very close to zero for BTC/AUD and BTC/CAD returns.

Table 1 **Summary statistics, exchange rate returns and volatility**

Cross-market exchange rate							
(a) Returns	**Mean**	**St. Dev.**	**Median**	**Max**	**Min**	**Skewness**	**Kurtosis**
BTC/USD	0.307	4.929	0.225	30.83	-34.54	-0.357	11.69
BTC/AUD	0.344	12.35	0.205	116.7	-110.6	0.0326	22.75
BTC/CAD	0.321	22.31	0.276	172.5	-157.7	0.0315	14.38
BTC/EUR	0.308	5.776	0.266	77.29	-61.84	0.763	45.55
BTC/GBP	0.304	11.30	0.301	104.3	-105.4	-0.149	16.38
(b) Volatility							
BTC/USD	0.709	1.008	0.455	20.68	0	9.086	139.2
BTC/AUD	6.091	4.467	4.426	30.67	0.105	1.499	5.329
BTC/CAD	7.248	4.681	6.284	30.01	0	1.054	4.330
BTC/EUR	0.740	0.899	0.472	11.29	0.0698	4.899	39.67
BTC/GBP	9.298	6.378	7.688	69.04	0	2.639	17.65
Number of observations	1786						

All returns series display unequivocally leptokurtic behaviours with sample Kurtosis above 10 (up to 45 in the case of BTC/EUR), suggesting they have long tails representing occurrences of extreme events of highly variable magnitudes with a mass point around the central tendency. The latter observation is confirmed by the graphs presented in Figure 1. Overall, the BTC/USD and BTC/EUR returns series appear to be the most stable with maximum values of 30.8 and 77.3 for minima of -34.5 and -61.8, respectively, along with sample standard deviations at least twice as small as that of any other series under scrutiny. The BTC/CAD exchange rate returns exhibit the most widely spread distribution (minimum return of -157.7 for a maximum of 172.5) and are also characterised by the largest standard deviation in the sample (over 22). Plots in Figure 1 suggest that the instability of the BTC/CAD returns series is most notably due to the large number of extreme events since early 2017, a feature that is noticeable in the BTC/AUD returns too, and also on the BTC/USD market, though to a lesser extent. At a glance, graphs in Figure 1 reveal frequent bouts of highly volatile returns which seem to be fairly evenly distributed on either side of their long run central tendencies, with the BTC/USD and BTC/EUR markets being the most stable.

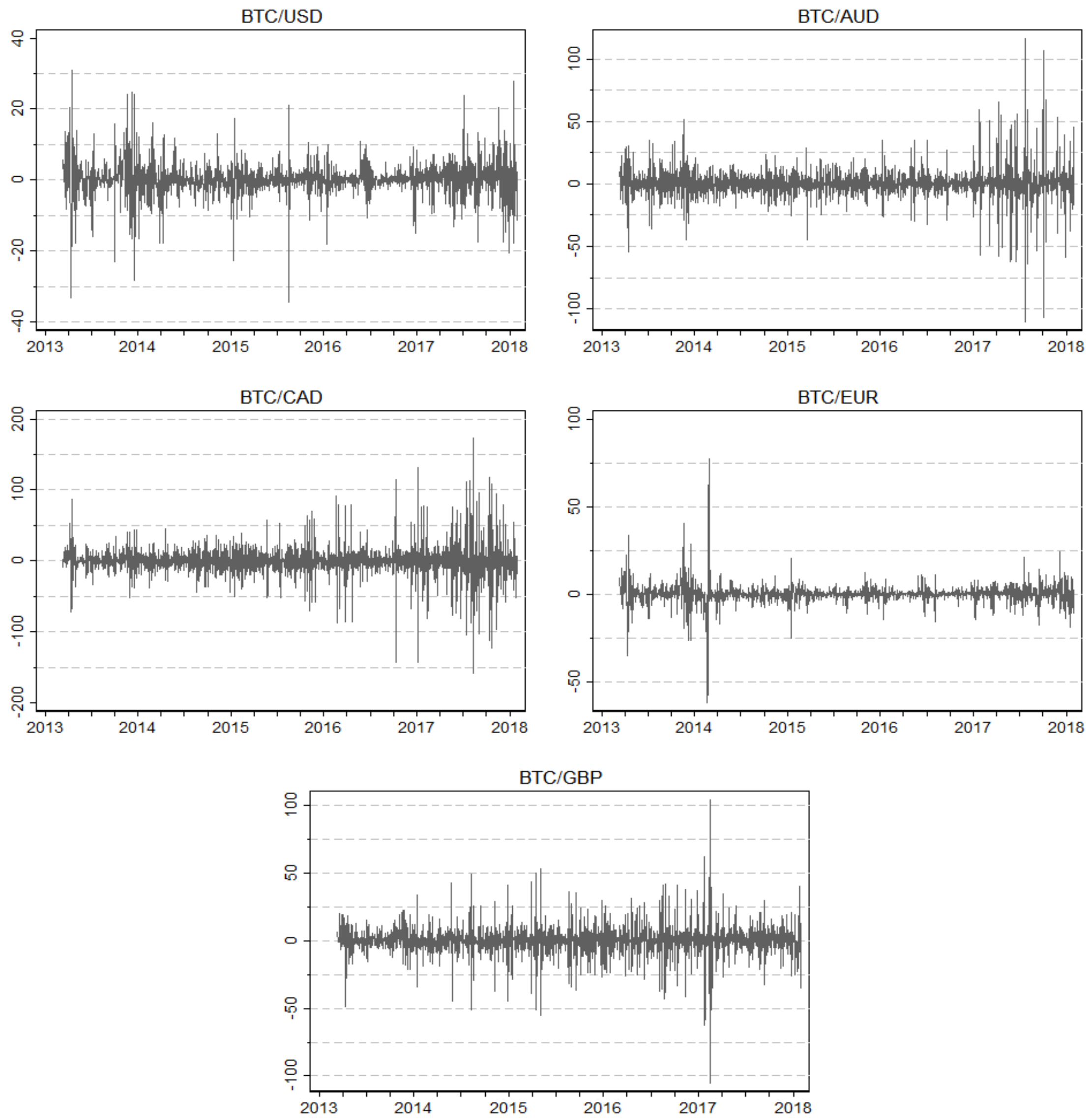
The summary statistics of cross-market exchange rates volatility (lower panel of Table 1) comfort our previous intuitions. The average volatility of BTC/USD and BTC/EUR settles at around 0.7 and is smaller than that of other exchange rates by one order of magnitude (from around 6 for BTC/AUD to over 9 for BTC/GBP). Furthermore, the two aforementioned series exhibit much larger positive skews and higher Kurtosis than their counterparts, and such lepotkurtic and heavily right skewed distributions suggest that these markets are less prone to unusually high levels of volatility. That is, observations concentrate to the left of the distribution close to the central tendency (recall that volatility is always positive).

While confirming that the BTC/USD and BTC/EUR markets are the most stable over the period of study, Table 1 strengthens the idea that the BTC/GBP has experienced the most extreme occurrences of high uncertainty, as witnessed by the scale of the y-axis on the graph presented in Figure 2. Interestingly, the series plotted in Figure 2 show a seemingly upward trend in the volatility of BTC/CAD over time which also appears in BTC/AUD volatility from the end 2016 on. An apparent increase in average volatility also appears on the three other markets in 2017 and early 2018, although to a lesser extent.

3 Methodology

We follow the generalized variance decomposition approach developed in Diebold and Yilmaz (2012) in order to estimate returns and volatility spillovers across the five markets under scrutiny. This methodology provides both static and dynamic measures of spillovers, and several papers have used a similar empirical framework analyse the interconnectedness

Figure 1 **Exchange rate returns**

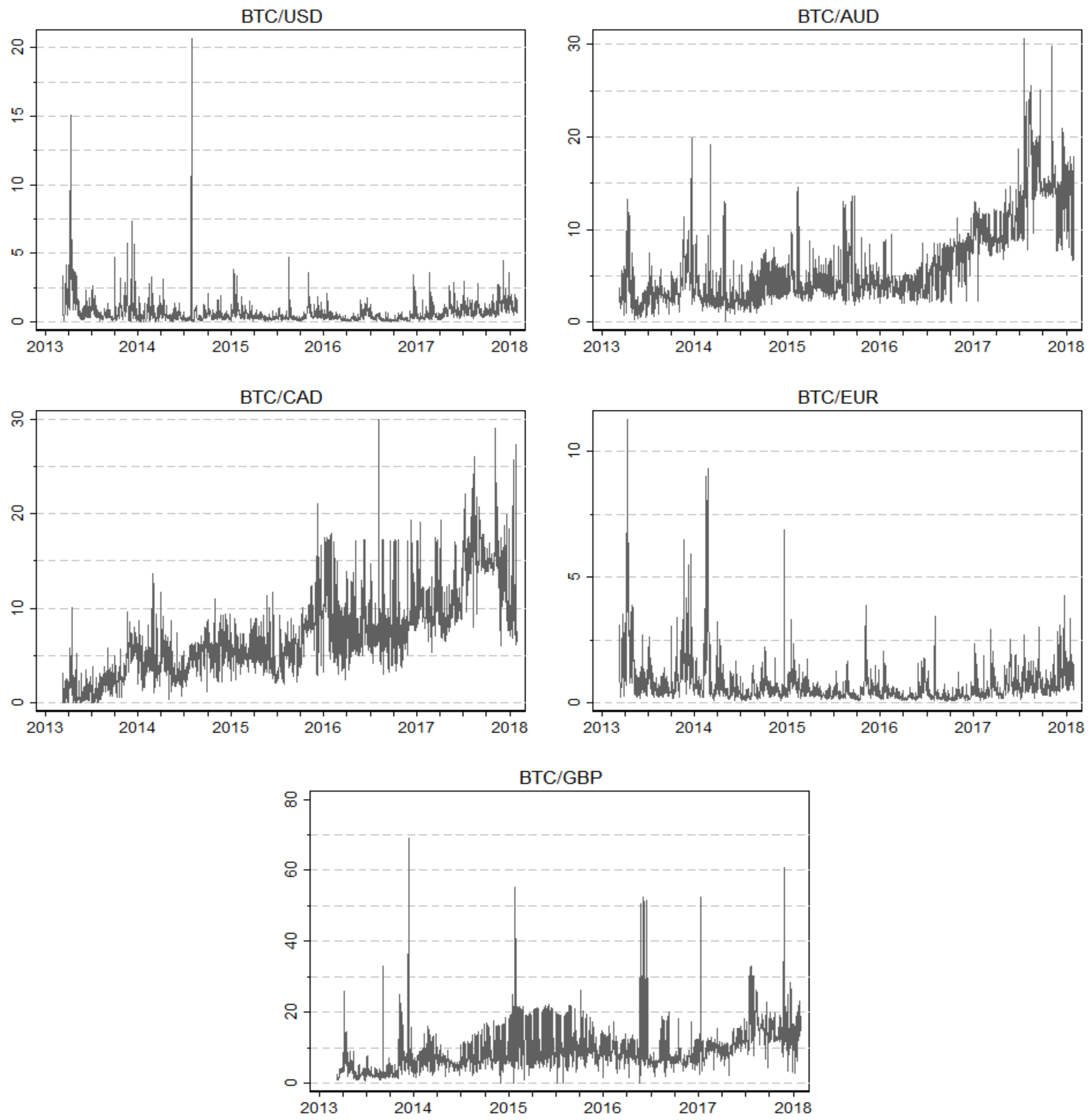


Note: Exchange rate returns series, daily. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

of financial markets (e.g. Corbet, Meegan, et al., 2018; Fernández-Rodríguez et al., 2016; Lucey et al., 2014; Yarovaya et al., 2016). However, to the best of our knowledge no previous research has analysed cross-market returns and volatility spillovers on Bitcoin to currency exchange rates.

The variance decomposition approach to measuring return and volatility spillovers (first presented in Diebold and Yilmaz (2009)) exploits Cholesky factorisation methods. This produces orthogonal innovations as is typically required for variance decompositions in Vector Auto-Regressive (VAR) models, with the main drawback of being sensitive to variable ordering (Diebold & Yilmaz, 2009). Diebold and Yilmaz (2012) propose a so-called

Figure 2 **Exchange rate volatility**



Note: Exchange rate volatility series, daily. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

generalised variance decomposition (GVD) that allows them to alleviate the orthogonality condition altogether and to account for correlated innovations, hence improving on their previous effort by making their measure of spillovers invariant to the order of the variables in the system (Diebold & Yilmaz, 2012; Koop et al., 1996; Pesaran & Shin, 1998). Considering our case of investigation - the five market Bitcoin price system - the estimates of spillover are based on the following covariance-stationary VAR model:

$$y_t = \sum_{i=1}^{p} \mu_i \, y_{t-1} + \epsilon_t \tag{2}$$

where $y_t = (y_{1t}, y_{2t}, y_{3t}, y_{4t}, y_{5t})$ or is a (1×5) random vector of endogenous variables; μ is a (5×5) coefficient matrix; y_{t-1} is the previous realisation of y_t; and $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t}, \epsilon_{4t}, \epsilon_{5t})$ is an *i.i.d.* error term with $\epsilon_t \sim (0, \Sigma_\epsilon)$.

The VAR model in Equation 2 can be re-written as a moving average process as follows:

$$y_t = \sum_{i=0}^{\infty} \delta_i \epsilon_{t-i} \tag{3}$$

where (5×5) coefficient matrices δ_i depend on the recursion $\delta_i = \mu_1 \delta_{i-1} + \mu_2 \delta_{i-2} + ... + \mu_p \delta_{i-p}$ with δ_0 an identity matrix and $\delta_i = 0$ if $i < 0$.

The heart of the GVD approach is to generate the correlated shocks by using the past distribution of errors (Diebold & Yilmaz, 2012). Therefore, the h-step-ahead forecast error GVD matrix is given by:

$$\tau_{ij}^{g}(h) = \frac{\sigma_{ii}^{-}1 \sum\limits_{h=0}^{h-1} (e_i' \, \delta_h \, \Sigma \, e_j)^2}{\sum\limits_{h=0}^{h-1} (e_i' \, \delta_h \, \Sigma \, \delta_h' \, e_j)} \tag{4}$$

where e_i is the selection vector with its i^{th} element equal to one and zeros otherwise; δ_h is the coefficient matrix times the h-lagged shock vector; Σ is the variance matrix of the error vector ϵ; and σ_{ii} is the i^{th} diagonal element of Σ.

The shocks generated through Equation 4 are not required to be orthogonal, so the sum of forecast error variance contributions are not equal to one, i.e. $\sum\limits_{j} \tau_{ij}^{g}(h) \neq 1$. To make their method more operational, the authors propose to normalise the above variance shares as follows:

$$\tilde{\tau}_{ij}^{g}(h) = \frac{\tau_{ij}^{g}(h)}{\sum\limits_{j=1}^{N} \tau_{ij}^{g}(h)} \tag{5}$$

where g is the order of the system (such as five market system as in our case), $\sum\limits_{j=1}^{N} \tilde{\tau}_{ij}^{g}(h) = 1$ and $\sum\limits_{i,j=1}^{N} \tilde{\tau}_{ij}^{g}(h) = N$.

The quantities in equation 5 can then be used directly to estimate several measures of interest as follows:

- **Total spillover**:

$$S.O^g(h) = \frac{\sum\limits_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\tau}^g_{ij}(h)}{\sum\limits_{i,j=1}^{N} \tilde{\tau}^g_{ij}(h)} \times 100 = \frac{\sum\limits_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\tau}^g_{ij}(h)}{N} \times 100 \tag{6}$$

- **Directional spillover**:

  The following quantity measures the extent to which variable i is influenced by volatility shocks received from all other variables:

$$S.O^g_{i\,.}(h) = \frac{\sum\limits_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\tau}^g_{ij}(h)}{\sum\limits_{j=1}^{N} \tilde{\tau}^g_{ij}(h)} \times 100 \tag{7}$$

  Similarly, the amount of volatility transmitted by variable i to the other variables in the system can be gauged as follows:

$$S.O^g_{.\,i}(h) = \frac{\sum\limits_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\tau}^g_{ji}(h)}{\sum\limits_{j=1}^{N} \tilde{\tau}^g_{ji}(h)} \times 100 \tag{8}$$

- **Net spillover**:

  Finally, subtracting volatility spillovers *from* other variables from the volatility spillovers *to* other variables gives a measure of net spillovers:

$$S.O^g_i(h) = S.O^g_{.\,i}(h) - S.O^g_{i\,.}(h) \tag{9}$$

In order to refine our empirical study, we also implement the methodology presented in Baruník and Křehlík (2018) that builds on a *spectral representation* of variance decompositions to identify connectedness amongst variables at various levels of frequency. That way, the authors extend the work of Diebold and Yilmaz (2012) by offering the possibility to explore the frequency dynamics in a system of variables and thus to estimate spillovers of heterogenous magnitudes at different frequencies. In other terms, the strength of cross-market connectedness can vary across the frequency domain, i.e. the influence of idiosyncratic shocks on other variables might be limited to the short run or have a long-run impact on connected markets.

4 Results

Having discussed thus far various approaches to estimate spillover effects, in this section, we discuss results to shed light on the predictive power of each Bitcoin market. The basis for our estimation of spillovers are VAR models for daily returns and exchange rate volatility. We use Akaike's Information Criterion (AIC) to decide on the number of lags to include, and confirm its adequacy with Lagrange multiplier autocorrelation tests after VAR estimation. We chose a VAR order 17 and 7 for returns and volatility series, respectively. The Generalised Variance Decomposition is then carried out for 30-day-ahead forecasts.

We comment on the results for volatility spillovers and returns spillovers in two distinct sub-sections. Indeed, the former provide indications as to which components of the system are closely connected to each other given their sensitivity to one another's uncertainty. Returns spillovers, however, reveal more precise information regarding which components of the system are most important in *predicting* future price movements on other markets. Each set of results includes a full sample *static* analysis broken down into *directional connectedness* (from applying the method of Diebold and Yilmaz (2012)) and *frequency domain connectedness* (following Baruník and Křehlík (2018)), the latter allowing to refine the former by providing a decomposition of time-frequency dynamics of returns and volatility spillovers. However, in a full sample analysis the alternation of positive and negative extreme events typical of financial markets – some short-lived and others more persistent that can generate important downturns or speculative bubbles – tends to be smoothed over time. Therefore, we complement our results by carrying out an analysis similar to the former on a sub-sample of the data that is rolled over one day at a time to obtain a picture of *dynamic spillovers*. This methodology suggested by Diebold and Yilmaz (2012) allows to gauge how the strength of cross-market connectedness evolves over time. We use a 150-day rolling window. Finally, various robustness checks are discussed in the third sub-section.

4.1 Volatility spillovers

Table 2 displays results of the full sample analysis on directional, net and total spillovers for exchange rate volatility. The markets under consideration exhibit a non-trivial degree of interconnectedness with a *total spillover index* (TSI) of 15.78%. It appears that volatility shocks to the BTC/EUR and BTC/USD markets are the most influential in their contribution 'TO other' markets' volatility (24.8% and 25.9%, respectively), with BTC/AUD in third position (around 17%).

Table 2 **Volatility spillovers across five selected exchange rates in time domain**

	BTC/USD	BTC/AUD	BTC/CAD	BTC/EUR	BTC/GBP	Directional FROM others
BTC/USD	79.16	4.15	0.45	15.32	0.92	20.84
BTC/AUD	4.26	84.40	3.87	6.67	0.79	15.60
BTC/CAD	0.30	6.63	89.99	1.82	1.26	10.01
BTC/EUR	20.74	4.75	0.88	72.17	1.47	27.83
BTC/GBP	0.63	1.39	1.62	0.98	95.37	4.63
Directional TO others	25.93	16.92	6.82	24.79	4.45	*TSI: 78.90/500 = 15.78%*
Net spillovers	5.09	1.32	-3.19	-3.04	-0.18	

Note: Exchange rates volatility spillovers following Diebold and Yilmaz (2012). Numbers are percentages. “TSI” stands for Total Spillover Index.

4.1.1 Directional connectedness (static spillovers): Time domain analysis

Interestingly, the BTC/EUR market is also the most sensitive to uncertainty in other exchange rates (highest estimate in contribution ‘FROM others’), and the BTC/USD market the second most sensitive. In contrast, the BTC/GBP is by far the least influenced and least influential market in terms of volatility spillovers. BTC/CAD is also only loosely connected to the system, and is a bit more sensitive to other markets’ volatility than it is influential on others. Negative *net* volatility spillovers for the BTC/CAD and BTC/EUR exchange rates show that, overall, these markets tend to be net recipients of volatility. On the other hand, BTC/USD appears to be a net provider of volatility to the system, with net spillovers around 5%.

A closer look at pairwise spillovers reveals that the strongest bilateral relationship is to be found between the BTC/EUR and BTC/USD exchange rates, with volatility spillovers of about 15% from the former to the latter and little above 20% in the other direction. Both markets also display a non-trivial relationship with BTC/AUD – albeit of lesser intensity – which is almost symmetric in the case of BTC/USD (spillovers little above 4% in either direction) and slightly asymmetric in the case of BTC/EUR with its influence on BTC/AUD (around 6.7%) exceeding its sensitivity (little below 5%). Note that BTC/AUD is also a net provider of volatility to BTC/CAD – for which it is the main partner – and to BTC/GBP, although pairwise spillovers involving the latter never even reach 2%.

In sum, among the five markets under consideration BTC/EUR is the “most” connected one, with BTC/USD close second, while BTC/GBP appears to be the most isolated market. The pair BTC/EUR - BTC/USD are the most closely interlinked exchange rates, with about 15% to 20% of the forecast error variance in either variable’s volatility being explained by innovations in the other. Results also suggest that BTC/AUD might work as an intermediary allowing volatility to circulate between the main components of the system, i.e. BTC/USD and BTC/EUR, and the more isolated markets, namely BTC/CAD and BTC/GBP.

4.1.2 Frequency domain analysis of static spillovers

Table 3 refines the previous empirical results by providing a decomposition of time-frequency dynamics of volatility spillovers. The top panel considers *short* horizons (less than 4 days), while the bottom panel is concerned with *long* horizons (4 days or more).

Table 3 **Volatility spillovers across five selected exchange rates in frequency domain**

(a) *Short horizon*

	BTC/USD	BTC/AUD	BTC/CAD	BTC/EUR	BTC/GBP	FROM others
BTC/USD	35.09	0.38	0.08	3.91	0.16	4.52
BTC/AUD	0.19	23.94	0.23	0.39	0.08	0.88
BTC/CAD	0.07	0.43	42.71	0.35	0.12	0.96
BTC/EUR	2.64	0.39	0.09	22.93	0.11	3.24
BTC/GBP	0.15	0.22	0.14	0.22	58.48	0.74
TO others	3.05	1.42	0.54	4.87	0.47	*TSI: 10.34/193.49 = 5.34%*

(b) *Long horizon*

	BTC/USD	BTC/AUD	BTC/CAD	BTC/EUR	BTC/GBP	FROM others
BTC/USD	44.07	3.77	0.37	11.41	0.77	16.32
BTC/AUD	4.08	60.46	3.64	6.28	0.71	14.71
BTC/CAD	0.23	6.20	47.28	1.47	1.14	9.05
BTC/EUR	18.09	4.36	0.79	49.25	1.35	24.59
BTC/GBP	0.48	1.17	1.48	0.75	36.89	3.89
TO others	22.88	15.50	6.27	19.92	3.98	*TSI: 68.55/306.51 = 22.37%*

Note: Volatility spillovers, frequency domain analysis following Baruník and Křehlík (2018). *Short* and *Long* horizons refer to '4 days or less' and 'more than 4 days', respectively. Numbers are percentages.

The top panel of Table 3 shows that overall volatility spillovers in the system are around 5.3% when considering a short time horizon. In line with previous results, BTC/USD and BTC/EUR are the main providers and recipients of short-lived volatility shocks in the system, as well as each other's most influential counterpart, although in this instance BTC/EUR (BTC/USD) is a net provider (recipient) of volatility to BTC/USD (from BTC/EUR) and to (from) the system as a whole.

The bottom panel of Table 3 suggests that interconnectedness in the system is much stronger in the long run, with overall volatility spillovers above 22% for volatility. The earlier pattern of results is once again repeated, and BTC/EUR and BTC/USD are by far the most influential components of the system and each other's privileged partner, with the former a net recipient and the latter a net provider of volatility. BTC/AUD remains the second favorite counterpart for each of the two main markets – albeit spillovers are of a much smaller magnitude (well below 5%) – and the most important partner of BTC/CAD. As expected, results confirm that BTC/GBP is rather isolated from the system regarding transmissions of either short-run or long-run volatility shocks.

4.1.3 Dynamic spillover effects: Rolling window estimates

(a) Overall spillovers

To study how volatility spillovers co-move with fluctuatins in uncertainty, we plot overall volatility spillovers in the system in Figure 3 along with a monthly index measuring global Economic Policy Uncertainty (EPU)[7]. The TSI ranges between 20% and 40% throughout most of the sample period. We observe a sharp drop from above 50% to below 20% between the first and third quarters of 2014, mirroring with a few months lag the sharp decline in EPU between the summer of 2013 and the spring of 2014. The slow upward trend in TSI from late 2014 until mid-2016 also mimics the overall rise in uncertainty over the same period. The highest values of EPU are found around mid- and late 2016 and early 2017, with an extremely volatile TSI between late 2016 and early 2018.

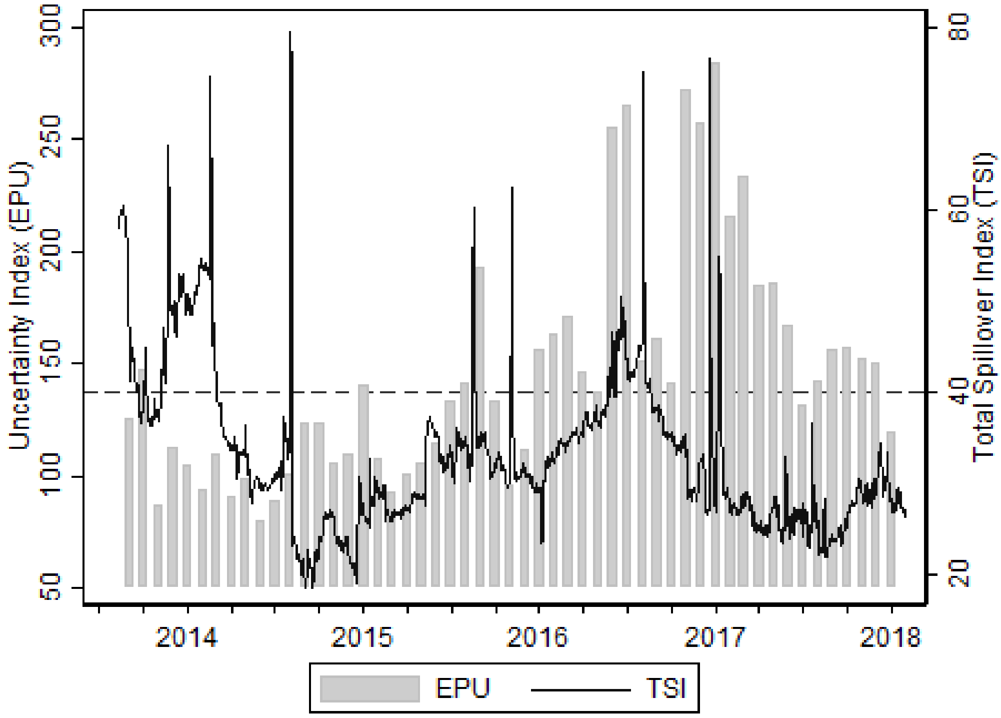
(b) Spillovers FROM and TO others

Volatility spillovers transmitted to other exchange rates, received from others, and net spillovers for each of the five markets under scrutiny are plotted in Figures 4, 5 and 6, respectively. The top left plot of Figure 4 confirms the role of BTC/USD as a big provider of volatility to the system over time, with spillovers to others routinely above 10%. Spillovers from BTC/EUR typically oscillate between 2% and 10% except for a 6-month period (2013Q4 and 2014Q1) where they often reach above 15%. Volatility spillovers from BTC/AUD also range between 0 and 10% and often exceed 5%, while those from BTC/CAD typically stay between 0% and slightly above 10%. Volatility shocks to BTC/GBP explain around approximatly 5% or less of volatility shocks on other markets during the sample period, except for short periods of time (in 2013Q3 and between 2016Q2 and 2016Q4) where they greatly exceed 10%.

As displayed in Figure 5, the sensitivity of the BTC/USD market to uncertainty shocks on other markets is highly volatile between 2013Q3 and 2014Q1 (spillovers ranging from 10%

[7] Data gathered from *http://www.policyuncertainty.com/*.

Figure 3 **Overall volatility spillovers (dynamic plot) and Economic Policy Uncertainty Index**



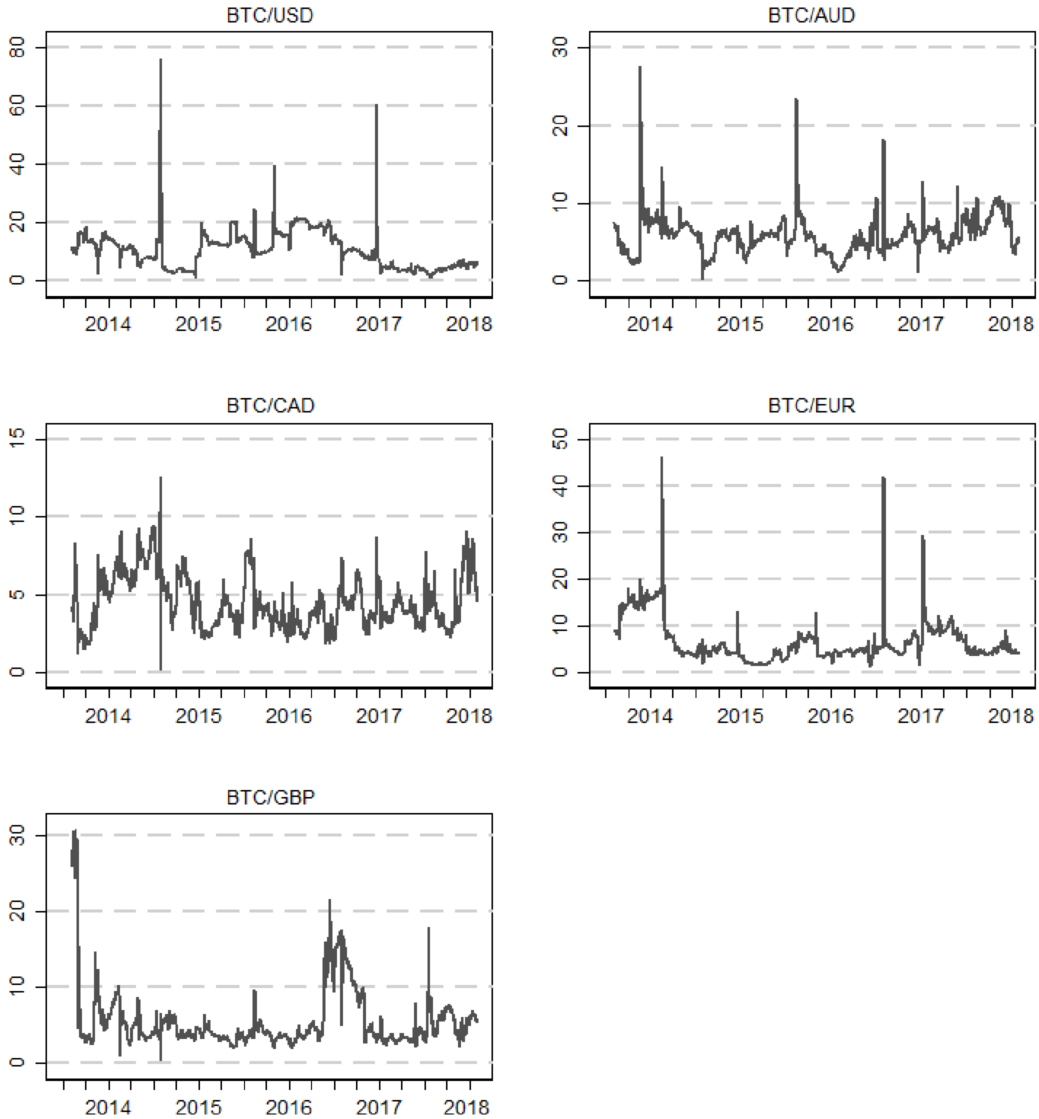
Note: Dynamic overall *volatility* spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window, right scale (percentages). Monthly Global Economic Policy Uncertainty (EPU) index, left scale. The dashed line shows the median value of EPU over the sample period. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

up to 20%) and more stable afterwards, with spillovers from others slowly declining down to 2.5% in 2014Q4 and remaining between that level and approximately 7% for most of the sample period. The evolution over time of spillovers from others to BTC/AUD resembles that observed for BTC/USD but is more stable, with spillovers from others to BTC/AUD concentrating between 4% and up 6% (approximately). Spillovers to BTC/EUR, however, remain volatile throughout the period under scrutiny and routinely exceed 10% while seldom going below 6%, albeit stabilising between approximately 4% and 7% starting in 2017Q1 until the end of the sample period. Spillovers to BTC/GBP from other markets oscillate between approximately 4% and 10% throughout the sample period, ranging most often between 5% and 10%. The sensitivity of BTC/CAD to volatility shocks on other markets features a similar profile to that of BTC/GBP albeit more unstable, with spillovers seldom below 5% and reaching more often above 10%.

(c) Net spillovers

The previously described patterns come together in Figure 6 to give a picture of the temporal evolution of net spillovers for each exchange rate considered in the present study.

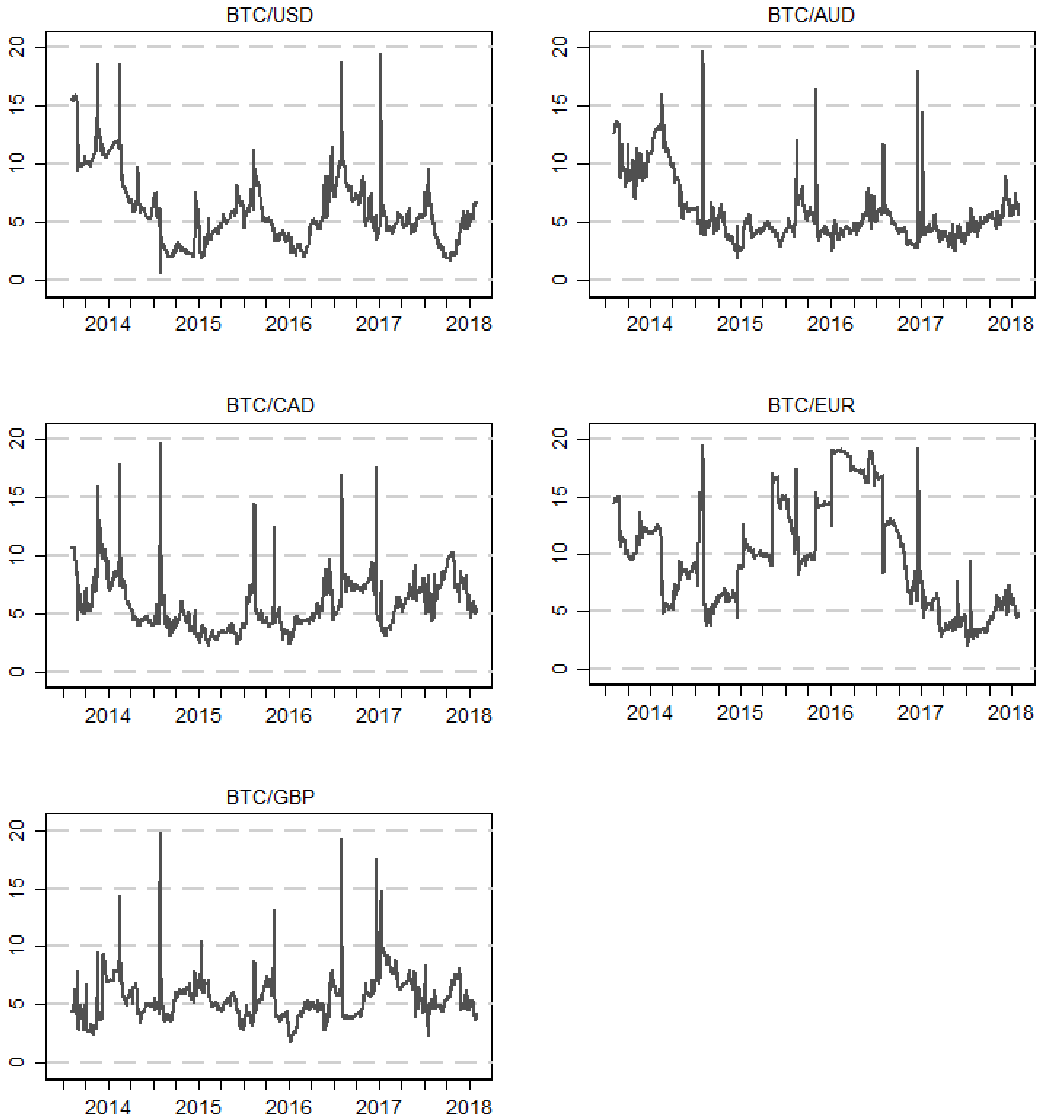
Figure 4 **Volatility spillovers to others: Dynamic plot**



Note: Dynamic volatility spillovers *to* others computed following Diebold and Yilmaz (2012) with a 150-day rolling window. Y-scales in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

We see at a glance that net spillovers tend to oscillate around zero over time, for all markets. Nonetheless, BTC/USD displays mostly positive net spillovers for the sample period, with a long period of exclusively positive values (from 2015Q1 to mid-2016) often around and above 15%. It tends to confirm the role of BTC/USD as a net provider of volatility to the system. Additionally, we identify three brief bouts of extremely high positive net spillovers for BTC/USD in early 2014Q3, early 2015Q4 and late 2016Q4. Interestingly, all other markets feature largely negative net spillovers during these events, making them

Figure 5 **Volatility spillovers from others: Dynamic plot**

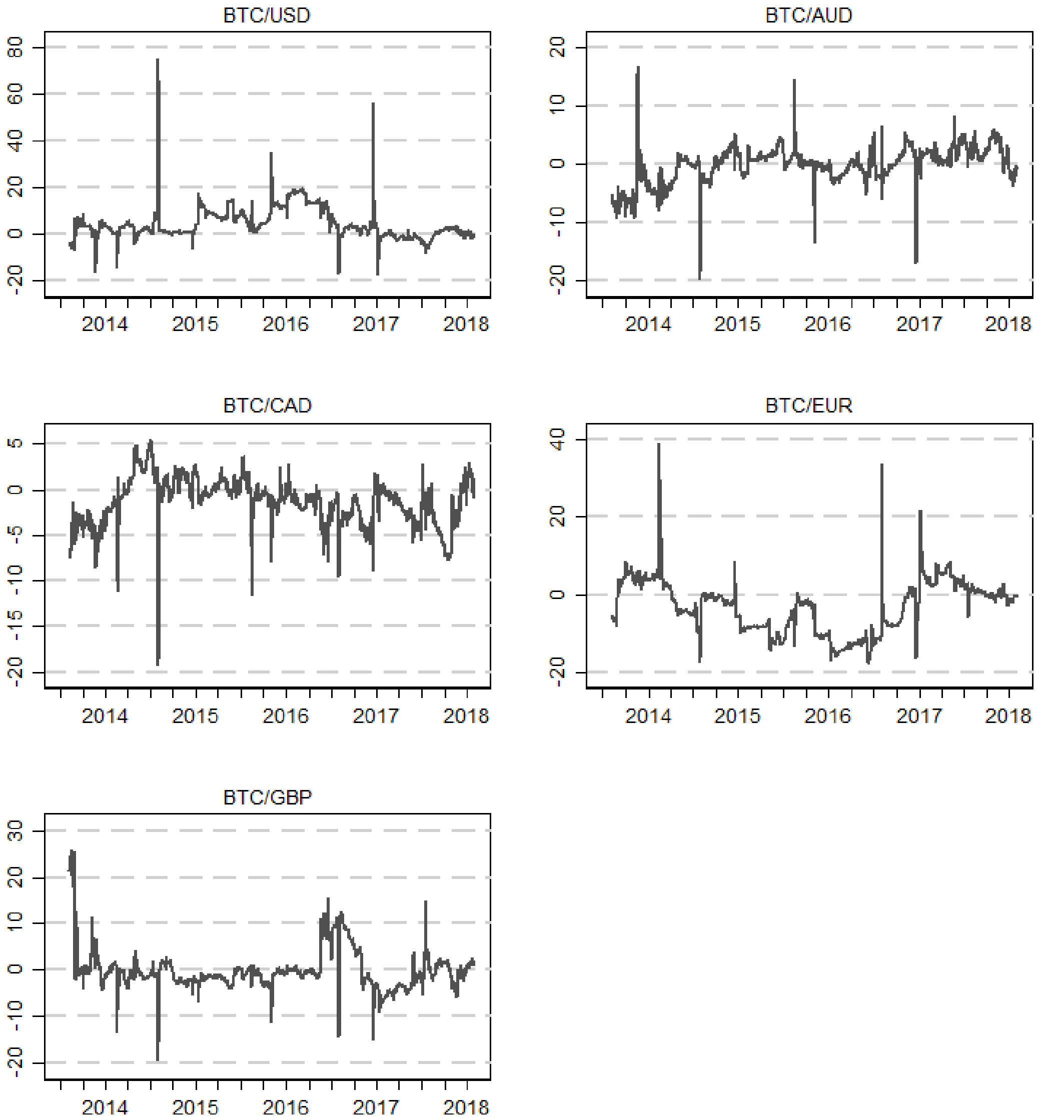


Note: Dynamic volatility spillovers *from* others computed following Diebold and Yilmaz (2012) with a 150-day rolling window. Y-scales in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

net receivers of volatility. This observation strengthens the idea that BTC/USD is central in the system as the prime source of uncertainty, with volatility shocks on that market strongly destabilising other exchange rates.

The middle right plot of Figure 6 clearly shows that BTC/EUR net spillovers are typically negative over the sample period and closely mirror those observed for BTC/USD, especially so during the period identified earlier (from 2015Q1 to mid-2016) when BTC/USD (BTC/EUR) net spillovers are consistently positive (negative) and large. This dynamic

Figure 6 **Net volatility spillovers: Dynamic plot**



Note: Dynamic *net* volatility spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window. Y-scales in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

spillovers plot ascertains the persistence over time of the role of BTC/EUR as a net recipient of volatility in the system, and also corroborates the "privileged" relationship between BTC/EUR and BTC/USD.

Net volatility spillovers from BTC/AUD are mostly negative between 2013Q3 and 2014Q2, but this market is typically a net provider of volatility throughout the rest of the sample period. In contrast, net spillovers for BTC/CAD are mostly negative over time, with a pattern mirroring that of BTC/AUD and reminding us of the close relationship between both markets uncovered from the full sample (static) analysis. The BTC/GBP market is characterised by surprisingly high positive net spillovers at the start of the sample period, for a brief amount of time, before experiencing small negative net spillovers most of the time with the exception of the period 2016Q2 - 2016Q4 when net spillovers are again large and positive (with one brief event of extreme negative values corresponding to a bout of high volatility transmission from BTC/USD).

To summarise findings so far, it appears that connectedness between Bitcoin-to-currency exchange markets reflects overall uncertainty. Trading on Bitcoin markets depends largely on investor sentiment, and a lack of confidence eventually heightens volatility on these markets which become more intensely interlinked as investors diversify to mitigate risks pertaining to a particular market. In that respect, BTC/USD is likely a prime source of volatility for the system. Indeed, volatility to BTC/USD and BTC/EUR are the most influential in predicting the volatility of other exchange rates (Figure 4), and the BTC/EUR volatility tends to be the most sensitive to innovations on other markets (Figure 5). Additionally, the BTC/USD exchange rate is typically a net provider of volatility, which is mirrored by the tendency of the BTC/EUR market to be a net receiver in its connection to other markets, while the influences to and from others for the other three exchange rate volatility series tend to even out (Figure 6). Note that Figure 6 displays net spillovers that get notably closer to zero over 2017 and in early 2018, especially so for BTC/USD and BTC/EUR.

As was previously stated, we interpret volatility spillovers as being indicative of the *intensity* of cross-market connectedness in the system. In the next section we turn to the results pertaining to exchange rates returns spillovers that contain information on the predictive power of price movements on a given market in influencing prices on other markets.

4.2 Returns spillovers

4.2.1 Directional connectedness (static spillovers): Time domain analysis

Table 4 presents returns spillovers obtained from the full sample analysis using the method of Diebold and Yilmaz (2012). Returns on the markets under scrutiny feature a significant degree of interdependence reflected by an estimated TSI of 17.4%. Results confirm the predominance of BTC/USD and BTC/EUR in the system, with returns spillovers to other markets of almost 23% and above 24%, respectively. Unexpected changes in returns on the BTC/AUD and BTC/GBP markets contribute roughly the same share of explanatory power in determining forecast error variance in other markets' returns (14.2% and 16.2%, respectively). In the meantime, returns to BTC/EUR are by far the most sensitive to innovations in other markets' returns (31% spillovers from others), while returns on the BTC/USD, BTC/AUD and BTC/GBP markets exhibit about twice as little sensitivity (spillovers from others around 16%).

Table 4 **Returns spillovers across five selected exchange rates**

	BTC/USD	BTC/AUD	BTC/CAD	BTC/EUR	BTC/GBP	Directional FROM others
BTC/USD	83.58	2.36	1.69	9.60	2.77	16.42
BTC/AUD	3.17	83.97	2.82	5.73	4.32	16.03
BTC/CAD	1.82	1.87	92.54	2.15	1.63	7.46
BTC/EUR	14.26	6.49	2.89	68.92	7.44	31.08
BTC/GBP	3.73	3.50	2.10	6.72	83.95	16.05
Directional TO others	22.97	14.22	9.50	24.19	16.17	*TSI: 87.05/500 = 17.41%*
Net spillovers	6.55	-1.81	2.04	-6.89	0.12	

Note: Exchange rates returns spillovers following Diebold and Yilmaz (2012). Numbers are percentages. "TSI" stands for Total Spillover Index.

The above observations establish BTC/USD as having the most predictive power in the system with net spillovers above 6%, and returns to BTC/EUR as experiencing a net influence from unexpected price movements on other markets (negative net spillovers of almost 7%). Returns to BTC/GBP are altogether as influential as they are sensitive, and returns to BTC/AUD are characterised by small negative net spillovers. Note that BTC/CAD displays small positive net spillovers (around 2%) but its returns are only loosely connected to the system (spillovers to and from others below 10%).

Pairwise returns spillovers show a pattern in line with volatility spillovers discussed earlier: BTC/EUR is typically the most influential partner of every other exchange rate, a fact particularly salient for the BTC/USD and BTC/GBP markets. Additionally, returns to BTC/EUR are especially sensitive to innovations in returns to BTC/USD, the latter therefore holding a net predictive power in that relationship. Other noticeable relationships are BTC/EUR - BTC/GBP – spillovers around 7% in either direction with a small (below 1%) net positive spillover for the second – and BTC/EUR - BTC/AUD – spillovers around 6% in either direction, again with a small (below 1%) net positive spillover for the second. All bilateral relationships involving BTC/CAD display pairwise spillovers below 3%.

This first glance at returns spillovers comforts the idea that the previously identified connectedness (through volatility spillovers) between BTC/USD and BTC/EUR matters, in that the former market holds a net predictive power in determining price movements on the latter. Actually, shocks to BTC/USD returns are the most influential in the system as a whole, and BTC/EUR returns are the most sensitive to shocks on other markets. Note that BTC/GBP is more strongly connected to the system in terms of returns spillovers that it is in terms of volatility. This is likely due to the range of variations in the BTC/GBP returns series being consistent with that of other markets (Figure 1), whereas discrepancies are more prominent in the case for volatility series (Figure 2).

4.2.2 Frequency domain analysis of static spillovers

Table 5 provides a decomposition of time-frequency dynamics for the returns spillovers presented in Table 4. The top panel indicates that overall returns spillovers in the system are around 14.5% when focussing on short-term components of forecast error variances. The pattern of results is qualitatively similar to the previous case where BTC/USD and BTC/EUR are the most important providers of short-lived shocks to returns in the system, with the latter the most sensitive of such shocks. They are also each other's most influential counterpart, BTC/EUR being a net recipient of unexpected price movements from BTC/USD and from the system as a whole. We find again the previously observed almost symmetric relationships between BTC/EUR and BTC/GBP (spillovers around 5%) and between BTC/EUR and BTC/AUD (spillovers between 4% and 5%).

Table 5 **Returns spillovers across five selected exchange rates - Frequency domain analysis**

(a) *Short horizon*

	BTC/USD	BTC/AUD	BTC/CAD	BTC/EUR	BTC/GBP	FROM others
BTC/USD	64.96	1.52	1.35	5.78	1.89	10.54
BTC/AUD	2.07	81.66	2.66	4.29	3.64	12.66
BTC/CAD	1.50	1.59	90.51	1.50	1.39	5.98
BTC/EUR	9.15	4.96	2.51	53.60	5.73	22.35
BTC/GBP	2.40	2.77	1.75	4.68	81.17	11.59
TO others	15.12	10.83	8.26	16.25	12.65	*TSI: 63.11/435.01 = 14.51%*

(b) *Long horizon*

	BTC/USD	BTC/AUD	BTC/CAD	BTC/EUR	BTC/GBP	FROM others
BTC/USD	18.62	0.84	0.34	3.82	0.88	5.89
BTC/AUD	1.10	2.31	0.16	1.43	0.68	3.38
BTC/CAD	0.32	0.28	2.03	0.65	0.24	1.48
BTC/EUR	5.11	1.53	0.38	15.32	1.71	8.73
BTC/GBP	1.33	0.74	0.35	2.04	2.78	4.46
TO others	7.86	3.39	1.24	7.94	3.51	*TSI: 23.94/64.99 = 36.83%*

Note: Returns spillovers, frequency domain analysis following Baruník and Křehlík (2018). *Short* and *Long* horizons refer to '4 days or less' and 'more than 4 days', respectively.

The bottom panel of Table 5 ascertains the interdependence of returns across the five exchange rates under scrutiny by presenting an estimated TSI of close to 37% in the long run. There again, net predictive power is held by BTC/USD with regards to BTC/EUR and to the whole system, with BTC/EUR the largest provider and recipient of returns shocks to and from other markets. BTC/AUD and BTC/GBP are the other two favourite counterparts of BTC/EUR after BTC/USD, and BTC/CAD is confirmed to be the least influenced and least influential market in terms of returns spillovers.

4.2.3 Rolling windows analysis (dynamic spillover plots)

(a) Overall spillovers

The total spillover index for exchange rate daily returns is depicted in Figure 7 along with the monthly EPU index. In spite of a certain degree of volatility with values ranging from below 50% to almost 80%, it appears that the returns TSI in the system fluctuates around 60% for most of the sample period. We observe a decline in returns connectedness across markets between 2013Q4 and 2014Q3 (from 70% to little above 50%), before the TSI stabilises around 60% for the period 2014Q3 to 2016Q2, except for a high variable TSI in 2015Q3. The dramatic plunge over the second half of 2016 is compensated for in early 2017 and the TSI again fluctuates between 55% and 65% for the remainder of the sample period.

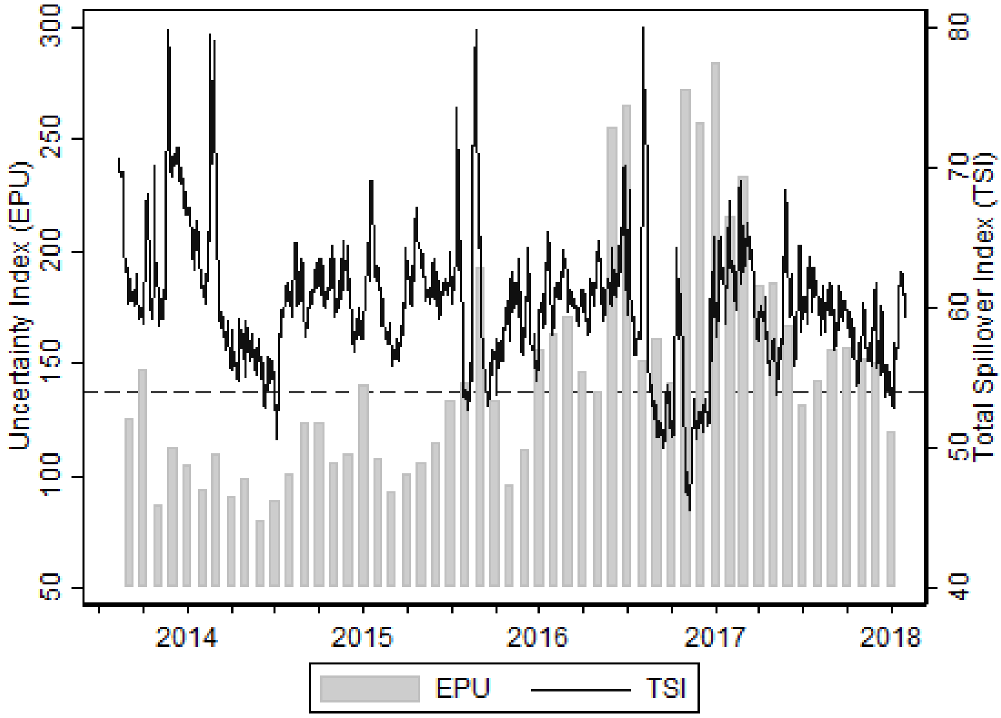
The plot confirms the strong interdependence of returns in the system over time (TSI almost always above 50%), and shows that it is fairly stable for the duration the sample period with no evident pattern suggesting its link to overall uncertainty. Although counter-intuitive, it is not incompatible with earlier results on volatility spillovers. Indeed, the latter were found to reflect the variations of global economic uncertainty, suggesting more strongly interconnected markets in times of high uncertainty. In spite of volatility transmitting more or less “easily” across components of the system depending on the economic climate, the capacity of returns shocks to help predict price movements on other markets remains stable over time in the system overall.

(b) Spillovers FROM and TO others

In the spirit of Diebold and Yilmaz (2012) dynamic spillovers are broken down into directional spillovers to other markets, from other markets, and net spillovers depicted in Figures 8, 9 and 10, respectively.

A quick glance at individual plots in Figure 8 reveals that the BTC/USD exchange rate exerts the biggest influence on other variables of the system, and that this influence strengthens in 2017 and early 2018. Interestingly, the influence of BTC/EUR returns shocks on other markets shifts downwards at the end of the sample period (from early 2017 on) after fluctuating around 5% to 7% most of the time. Returns spillovers from BTC/AUD,

Figure 7 **Overall returns spillovers (dynamic plot) and Economic Policy Uncertainty Index**



Note: Dynamic overall *returns* spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window, right scale (percentages). Monthly Global Economic Policy Uncertainty (EPU) index, left scale. The dashed line shows the median value of EPU over the sample period. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

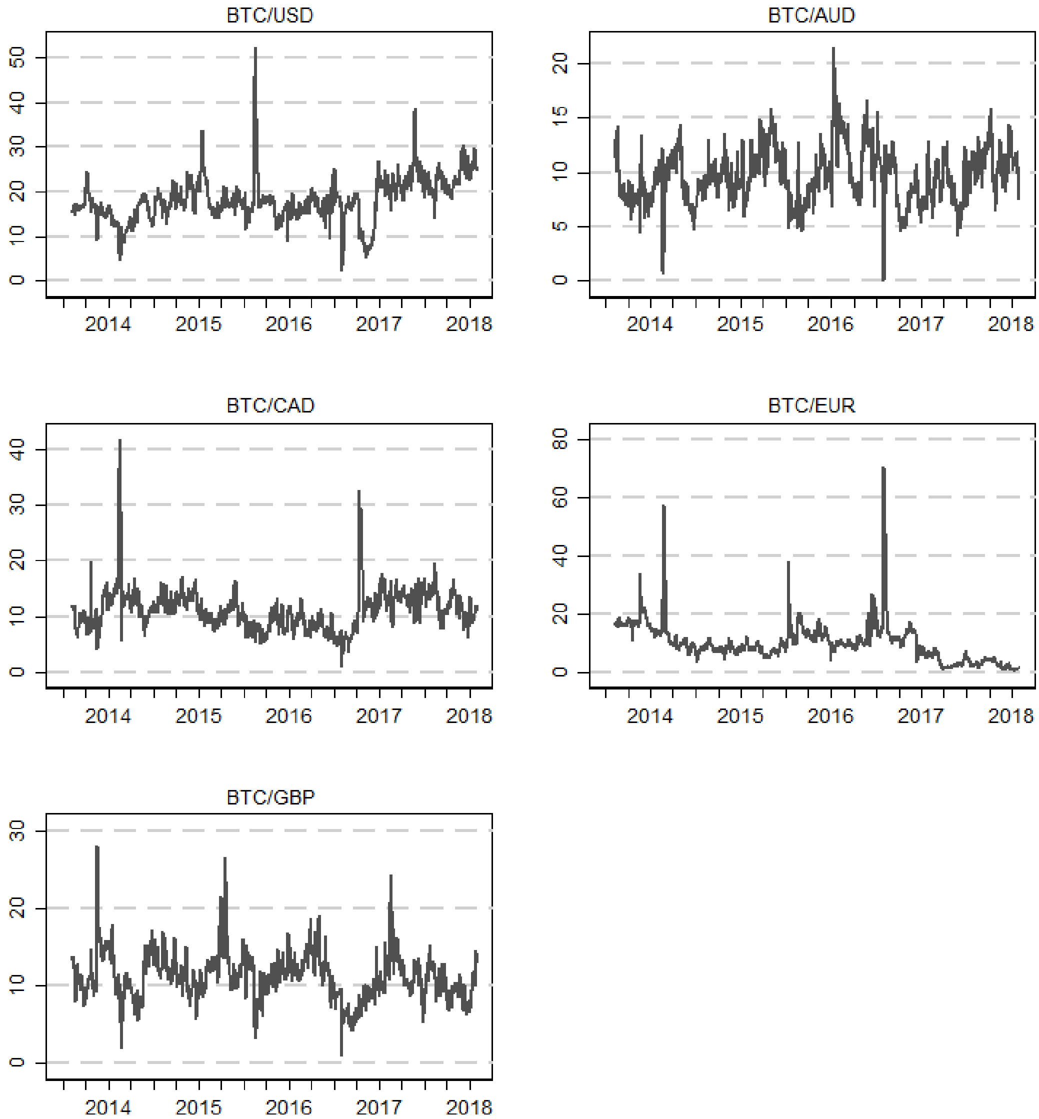
BTC/CAD and BTC/GBP to other markets are erratic but overall range between approximately 8% and 17% throughout the period under scrutiny.

Figure 9 indicates that BTC/USD returns are significantly influenced by shocks from other markets in late 2013 and early 2014 with spillovers between almost 13% and approximately 16%, while the latter then steady and fluctuate mostly in the range 6% - 14%. Returns spillovers received by BTC/AUD from other exchange rates range largely between 10% and 15%, as is the case for BTC/CAD and BTC/GBP. The share of forecasting error variance of BTC/EUR returns explained by innovations in other variables is almost systematically above 10% and routinely above 15%, and even larger than 15% between 2014Q2 and mid-2015 and after 2017Q1.

(c) Net spillovers

Dynamic net spillovers plotted in Figure 10 confirm the former intuition stemming from our full sample analysis. The BTC/USD exchange rate returns exhibit almost exclusively

Figure 8 **Returns spillovers to others, dynamic plot**

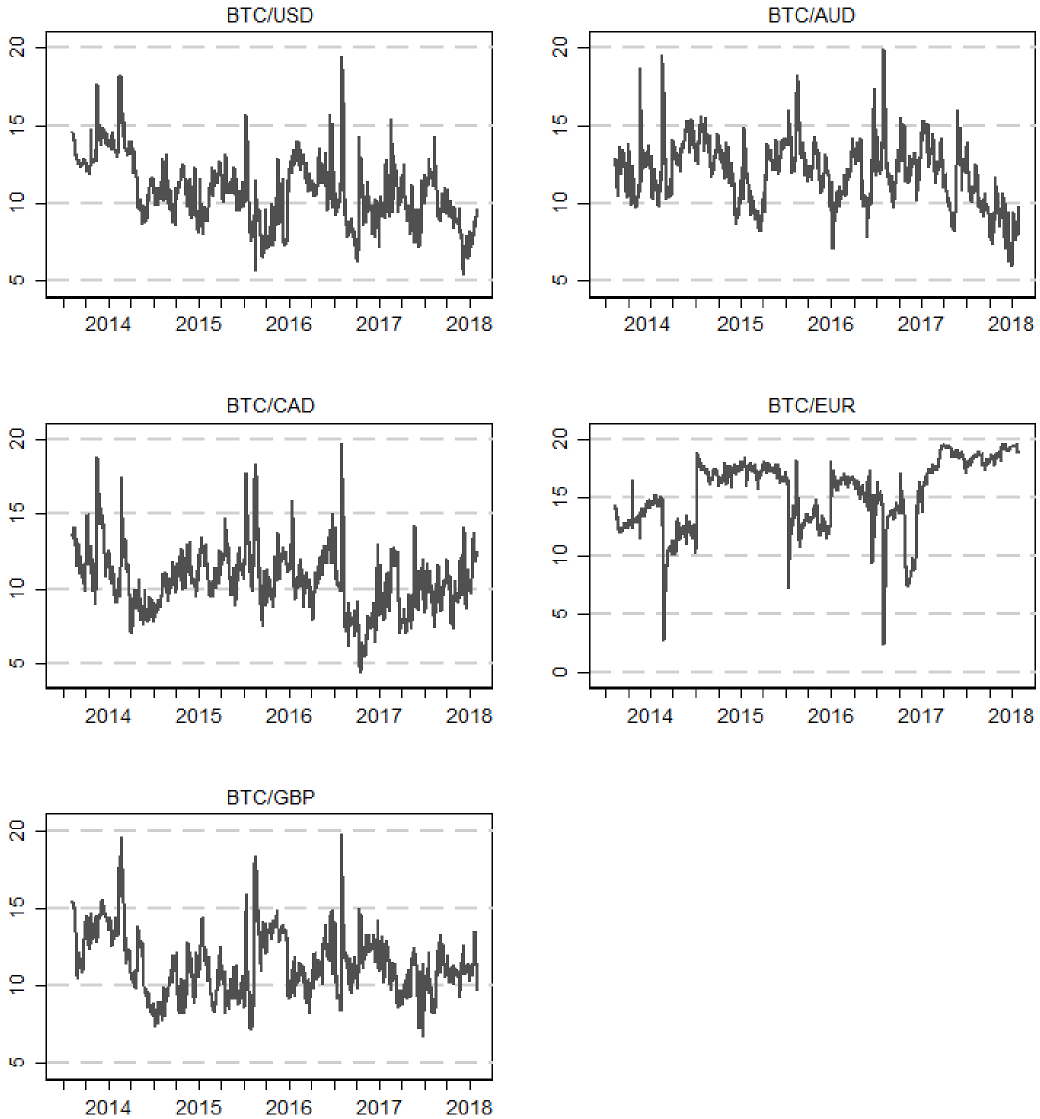


Note: Dynamic returns spillovers *to* others computed following Diebold and Yilmaz (2012) with a 150-day rolling window. Y-scales in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

positive net spillovers – reaching above 10% starting in early 2017–, representing the predictive power of shocks on the BTC/USD market in forecasting returns on other markets. Conversely, the BTC/EUR market is strongly connected to the system as a net receiver, i.e. mostly negative net spillovers that seem to mirror the BTC/USD ones over time with a marked decline starting in 2017Q1. The net connectedness of BTC/GBP returns is very erratic over time and incessantly crosses the zero line.

A similarly changeable pattern can be discerned for BTC/AUD, although its net spillovers

Figure 9 **Returns spillovers from others, dynamic plot**

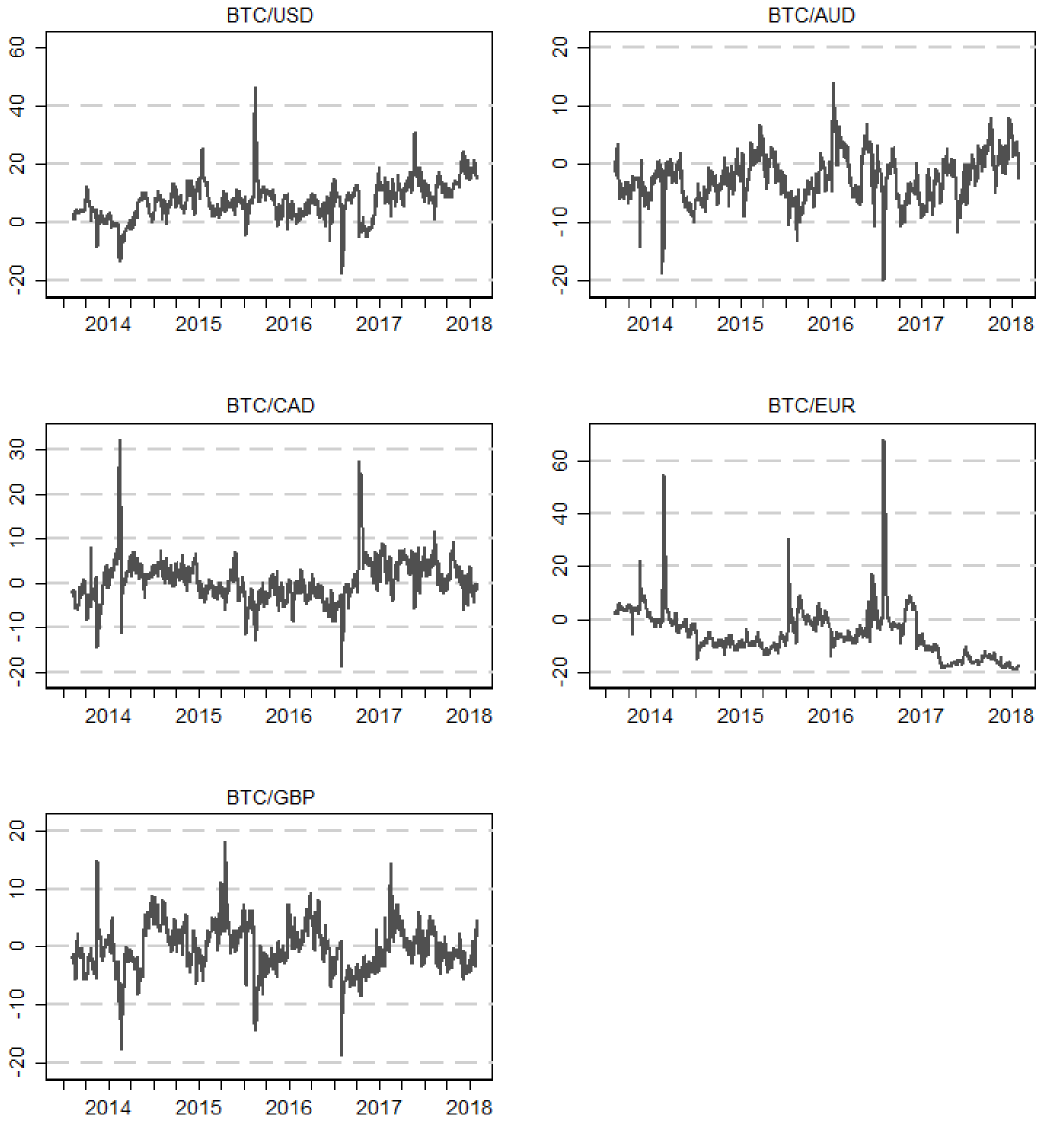


Note: Dynamic returns spillovers *from* others computed following Diebold and Yilmaz (2012) with a 150-day rolling window. Y-scales in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

are typically negative, characterising that market as usually predictable. Net returns spillovers from BTC/CAD slowly evolve around zero over time in a serpent-like fashion: negative in late 2013, positive in 2014, mostly negative from 2015Q1 to 2016Q4, and mostly positive for the remainder of the sample period. Their magnitude remains fairly small in absolute terms (seldom greater than 25%), reflecting the little influence of said market in predicting returns in the system.

In sum, results from our analysis of returns spillovers seem to complement nicely those

Figure 10 **Net returns spillovers, dynamic plot**



Note: Dynamic *net* returns spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window. Y-scales in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

commented on volatility spillovers. The BTC/USD and BTC/EUR are confirmed in their central roles in the system. They remain the most closely interlinked markets, and the former holds a net predictive power with regards to the system as a whole. That is, unexpected shocks in returns to BTC/USD embed information as to probable future shocks in prices on other markets, especially so for BTC/EUR. That relationship is the only one to be so dramatically asymmetric, the one between BTC/EUR and BTC/GBP, for instance, giving only a marginal advantage to the latter in terms of predictive power.

4.3 Robustness

How sensitive are our results to the choice of forecast horizon, window size, and alternative measure of volatility? In this section, we undertake robustness exercise in each aspect mentioned above.

4.3.1 Sensitivity to forecast horizon and window size for static and dynamic spillover system

We check the robustness of our full sample analysis results to the choice of the forecast horizon and the tuning of frequency bands that identify short- and long-run components of the forecast error GVD. Recall that our results are based on 30-days-ahead forecasts and that the time-frequency domain analysis consider the short horizon to be 4 days and the long horizon to be over 4 days. We performed similar estimations with 7-, 10-, and 60-days-ahead forecasts, and using 16 and 30 days to split frequency domains. The ensuing results (reported in the online appendix) corresponding to Tables 2, 3, 4 and 5 presented above produced very similar values for the estimated spillovers and yielded qualitatively identical conclusions.

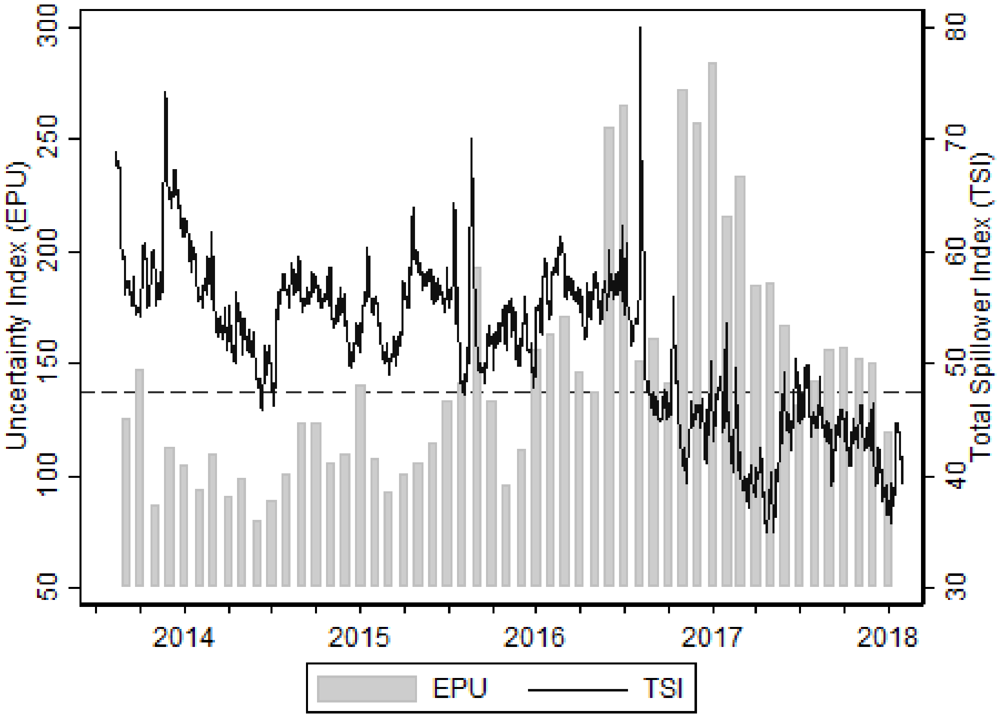
Next, Figures 11 and 12 (Figures 13 and 14) plot dynamic overall returns (volatility) spillovers using 15 days and 60 days as the forecast horizon for computing the GVD, respectively. We observe that the latter graphs are strongly consistent with Figure 7 (for return) (and Figure 3 for volatility, respectively) not only in the estimated values of the total spillover index, but also in the shape of the evolution that records the same extreme events in every case.

4.3.2 Alternative measures of volatility[8]

Recall that our empirical analyses are based on Parkinson's High-Low historical volatility (HL-HV) measure. This measure provides useful information regarding the future volatility than a close-to-close estimator. Garman and Klass (GK, 1980) proposed a volatility measure based on open (O), high (H), low (L) and close (C) prices to achieve better accuracy than previous estimators. Hence, as a robustness check, we use GK class of estimators and re-estimate spillover effects. The similarity between Parkinson and GK estimators are that both follow a geometric Brownian motion. However, drift and opening jumps are not treated in both models (Wiggins, 1991), but both estimators are 5 and 7 times respectively as powerful as the close-to-close measure (Garman & Klass, 1980; Parkinson, 1980). Recent studies have even gone further in extending GK volatility measure (among them

[8]Thanks to an anonymous referee who suggested Garman-Klass family of a measure of volatility for robustness exercise.

Figure 11 **Overall returns spillovers (dynamic plot – 15-day ahead forecast) and Economic Policy Uncertainty Index**



Note: Right scale (percentages): Dynamic overall *returns* spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window, using a 15-day ahead forecast. Left scale: monthly Global Economic Policy Uncertainty (EPU) index. The dashed line shows the median value of EPU over the sample period. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

see, for instance, Rogers-Satchell (OHLC) measure (Rogers & Satchell, 1991), GK-ABD volatilitiy measure (Alizadeh et al., 2002) and GK-YZ volatility measure (Yang & Zhang, 2000)[9]. These measures are summarised below:

$$GK = \Big\{0.5 \times (H_t - L_t)^2\Big\} - \Big\{(2Ln(2) - 1) \times (C_t - O_t)^2\Big\} \tag{10}$$

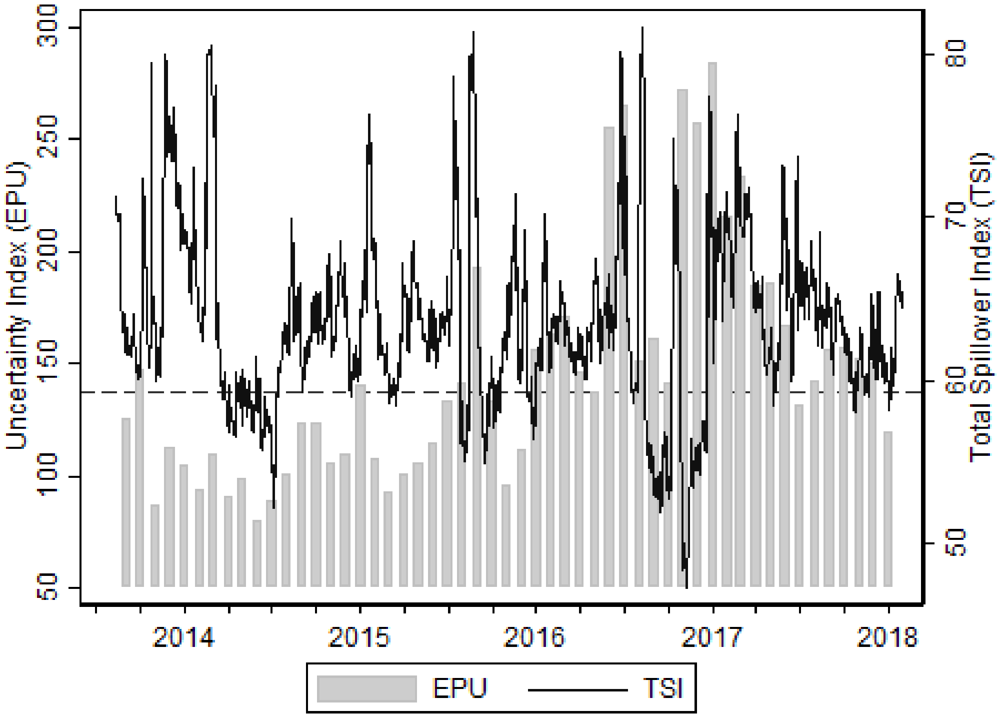
$$Rogers - Satchell = \big\{(H_t - C_t) \times (H_t - O_t)\big\} + \big\{(L_t - C_t) \times (L_t - O_t)\big\} \tag{11}$$

$$Yang - Zhang = (O_t - C_{t-1})^2 + 0.511 \times (H_t - L_i)^2 - (2Ln(2) - 1) \times (C_t - O_t)^2 \tag{12}$$

$$\begin{aligned} GK - ABD = 0.511 \times (H_t - L_t)^2 - 0.019 \times \Big\{&(C_t - O_t) \times (H_t + L_t - 2O_t) - 2 \\ &\times (H_t - O_t) \times (L_t - O_t)\Big\} - 0.383 \times (C_t - O_t)^2 \end{aligned} \tag{13}$$

[9]https://www.quantshare.com/itemd-197-trading-indicator-yang-zhang-extension-of or (Bennett & Gil, 2012)

Figure 12 **Overall returns spillovers (dynamic plot – 60-day ahead forecast) and Economic Policy Uncertainty Index**



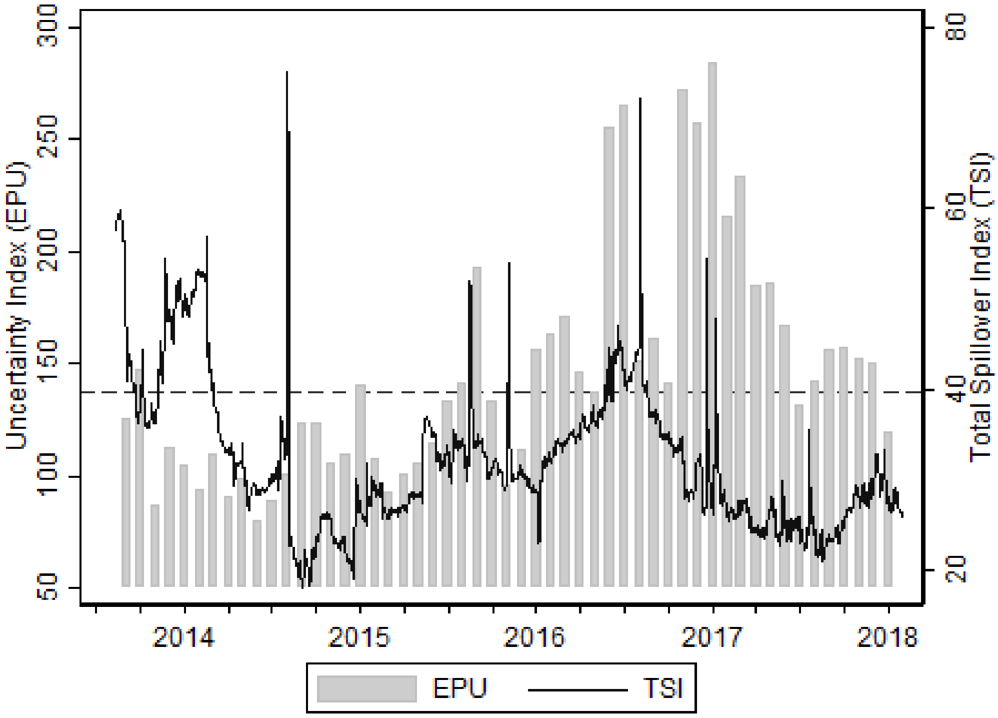
Note: Right scale (percentages): Dynamic overall *returns* spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window, using a 60-day ahead forecast. Left scale: monthly Global Economic Policy Uncertainty (EPU) index. The dashed line shows the median value of EPU over the sample period. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

The above measures compute the daily variance, so the corresponding estimate of the annualised daily percent standard deviation (volatility) is $Vol = \sqrt{365 * Variance}$.The summary statistics for the above measures are presented in Table 6.

We compute the static and dynamic volatility spillover based on Garman-Klass (GK) volatility. To begin with we compare the GK volatility measure with that of Parkinson (see Figure 15). As such, there is no significant differences in peaks and troughs and the fluctuations appear to co-move. In Tables 7 and 8 we have presented the overall spillover estimates from Diebold-Yilmaz and the frequency domanin approach of Barunik and Krehlik, respectively based on this measure of volatility.[10] Figures 16, 17, 18, 19, we have presented the dynamic volatility spillover effects (overall, from, to, and net, respectively). The results are consistent with the ones derived from Parkinson's measure. Hence, our conclusions on the predictive power (giver and the net receiver) remain unchanged to the use of an alternative measure of volatility.

[10]We have also estimated spillover effects from other class of GK measure of volatility, such as GK-YZ, etc. The results are available with the authors upon request.

Figure 13 **Overall volatility spillovers (dynamic plot – 15-day ahead forecast) and Economic Policy Uncertainty Index**

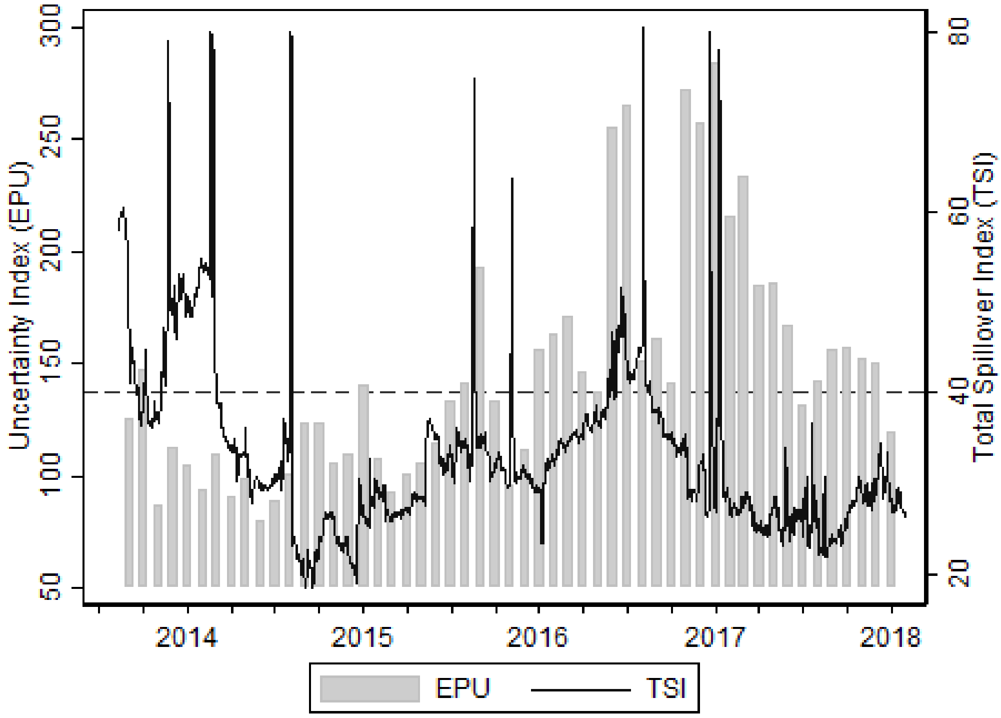


Note: Right scale (percentages): Dynamic overall *volatility* spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window, using a 15-day ahead forecast. Left scale: monthly Global Economic Policy Uncertainty (EPU) index. The dashed line shows the median value of EPU over the sample period. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

5 Conclusions

As long as economies' core are continually subject to frictions and are driven by incomplete information, it is nearly impossible to not experience spillover of shocks in some form or other. Depending on the net receiver or net dispenser of volatility, the magnitude of spillover effects represents vulnerability of a system to external shocks. The context of investigation in this paper, thus, has intermittent link to a broad economic and financial theory: as long as investors' choice of investment is governed by relative hedging value of an asset traded in various markets, they will invariably use estimates of spillover effects as the guiding information set to predict the next best investment strategy. Moreover, spillover effects in a market can be used as an indicator of relative market inefficiency. A weak-form cross-market inefficiency requires high-degree of spillover across markets where there is a clear indication of net receiver and net giver of volatility. This way, an investor can exploit arbitrage value by embedding the dynamic features of spillover in his prediction strategy. In this paper, we have created a first-hand information set for cryptocurrency investors by estimating spillover-effects in five markets where Bitcoin is highly traded.

Figure 14 **Overall volatility spillovers (dynamic plot – 60-day ahead forecast) and Economic Policy Uncertainty Index**

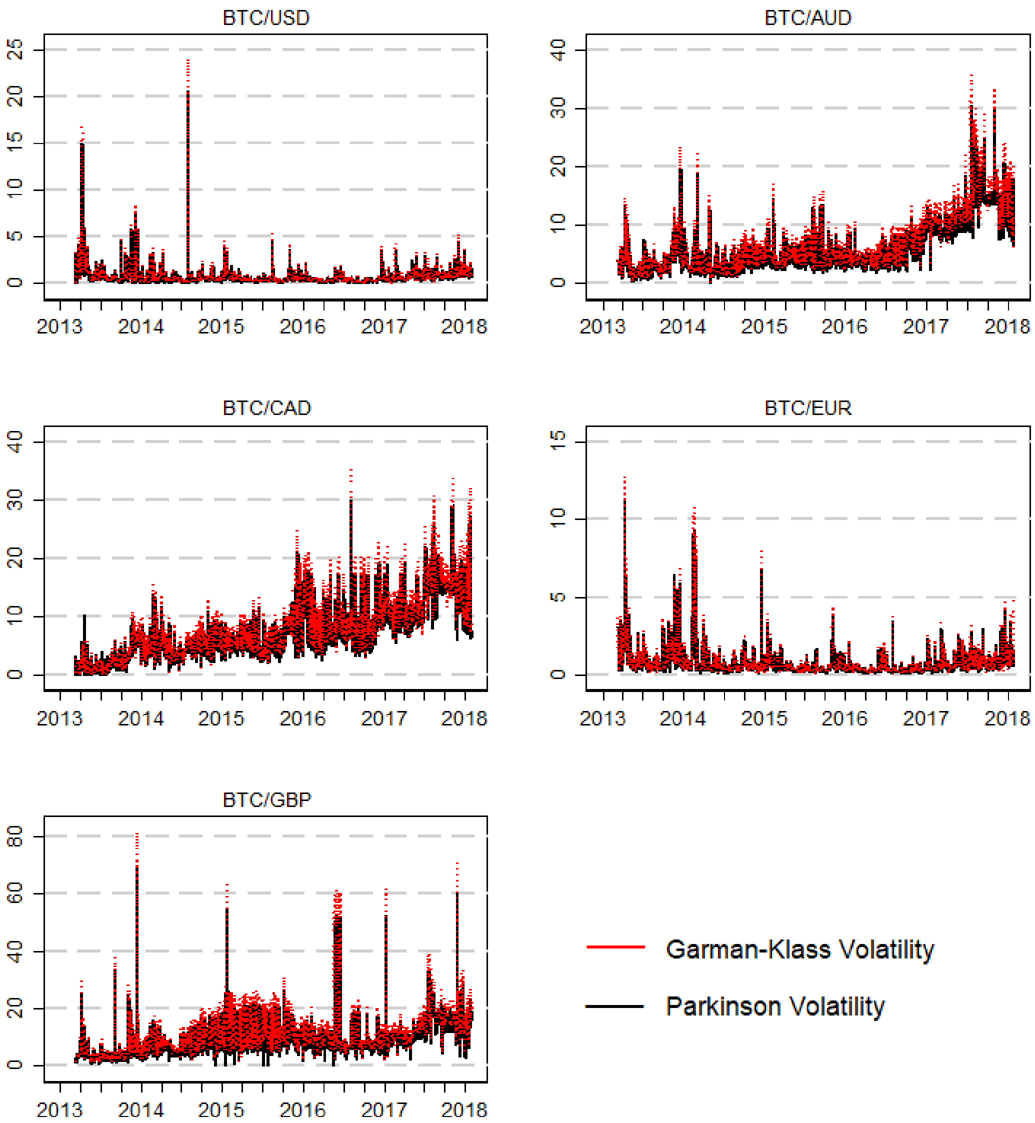


Note: Right scale (percentages): Dynamic overall *volatility* spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window, using a 60-day ahead forecast. Left scale: monthly Global Economic Policy Uncertainty (EPU) index. The dashed line shows the median value of EPU over the sample period. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

A unique aspect of our research concerns estimation of volatility spillover effects (with a better measure of volatility) *across* Bitcoin markets. We have investigated how spillover effects are governed by uncertainty episodes. With an aim to capture information asymmetry through fluctuations in uncertainty, our study sheds important insights on the dynamic interdependence of spillover effects during high/low uncertainty episodes. By doing this, we capture the *sentimental value*, researchers often attach to Bitcoin prices (in the absence of a dedicated asset pricing theory for cryptocurrency). By studying *cross-market* spillover in Bitcoin prices we have also complemented to a sparse body of literature (such as Cheah et al. (2018)) and have envisaged the importance of studying a systematic pattern of shocks' movement by capturing a 'system dynamics'. Because, as of now, price movements in Bitcoin market possess no (theoretical) policy bound for an effective control, a perhaps acceptable approach is to exploit 'system features' to provide a net predictive power.

Using the measure of volatility and well-established dynamic spillover methods, we have found that Bitcoin-USD holds high predictive power and Bitcoin-Euro acts as the net receiver. Moreover, higher uncertainty is found to accelerate spillover effects with larger impacts across markets. The results hold implications for cross-market dynamic inefficiency and predictive power of one market for tapping in the arbitrage conditions. Our results have implications for broad macroeconomic theory and investment decisions as envisaged by islands with sticky price information: investors of a risky asset like Bitcoin need a well-defined information set which would determine - at least in part - their expected return value. In that sense, our research holds significant predictive value for cryptocurrency investors.

Figure 15 **Comparison of GK and Parkinson Volatility Plots**



Note: Exchange rate volatility series, daily. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

Table 6 **Different Volatility measures across five selected exchange rates**

(a) BTC/USD volatility

	Mean	St. Dev.	Max	Min	Skewness	Kurtosis
Parkinson (H-L)	0.709	1.008	20.68	0.0	9.086	139.2
GK (OC-HL)	0.773	1.140	24.33	0.010	9.389	150.5
GK-ABD	1.323	2.043	24.57	0.004	4.353	30.20
Rogers-Satchell	2.206	2.835	33.42	0.0	3.033	18.10
GK-YZ	1.011	1.294	24.61	0.02	8.209	116.5

(b) BTC/AUD volatility

Parkinson (H-L)	6.091	4.467	30.67	0.105	1.499	5.329
GK (OC-HL)	7.025	5.247	35.96	0.112	1.507	5.391
GK-ABD	5.664	3.371	21.20	0.114	1.150	4.352
Rogers-Satchell	8.023	6.541	44.12	0.0	1.607	5.747
GK-YZ	7.437	5.375	36.71	0.140	1.504	5.317

(c) BTC/CAD volatility

Parkinson (H-L)	7.248	4.681	30.01	0	1.054	4.330
GK (OC-HL)	8.176	5.449	35.18	0	1.058	4.346
GK-ABD	6.639	3.887	34.73	0	1.082	5.646
Rogers-Satchell	9.369	6.906	47.28	0	1.273	4.994
GK-YZ	9.097	5.792	40.88	0	1.149	4.838

(d) BTC/EUR volatility

Parkinson (H-L)	0.740	0.899	11.29	0.069	4.899	39.67
GK (OC-HL)	0.794	1.043	12.72	0.007	5.001	40.09
GK-ABD	0.874	1.361	26.78	0.015	8.784	126.7
Rogers-Satchell	1.126	1.515	22.60	0.007	5.525	51.66
GK-YZ	1.052	1.266	14.27	0.104	4.561	32.73

(e) BTC/GBP volatility

Parkinson (H-L)	9.298	6.378	69.04	0	2.639	17.65
GK (OC-HL)	10.88	7.507	81.25	0.745	2.649	17.70
GK-ABD	10.85	7.569	80.01	0.753	2.657	17.66
Rogers-Satchell	14.92	10.73	109.1	0.0	2.506	16.32
GK-YZ	11.26	7.52	82.14	1.054	2.683	17.97

Note: GK: Garman-Klass (1980). GK-ABD: Garman-Klass extension, Alizadeh, Brandt and Diebold (2002). GK-YZ: Garman-Klass Yang-Zhang extinsion, Yang and Zhang, (2000). Rogers-Satchell (1991).

Table 7 **Volatility spillovers across five selected exchange rates: Garman-Klass measure**

	BTC/USD	BTC/AUD	BTC/CAD	BTC/EUR	BTC/GBP	Directional FROM others
BTC/USD	81.25	3.99	0.39	13.62	0.75	18.75
BTC/AUD	3.41	85.94	3.50	6.43	0.72	14.06
BTC/CAD	0.25	5.19	91.61	1.53	1.42	8.39
BTC/EUR	17.25	4.07	0.67	76.48	1.51	23.5
BTC/GBP	0.58	1.56	1.33	0.97	95.55	4.44
Directional TO others	21.49	14.81	5.89	22.55	4.4	*TSI: 69.14/500 = 13.83%*
Net spillovers	2.74	0.75	-2.5	-0.95	-0.04	

Note: Exchange rates volatility spillovers following Diebold and Yilmaz (2012). Numbers are percentages. "TSI" stands for Total Spillover Index.

Table 8 **Volatility spillovers across five selected exchange rates - Frequency domain analysis: Garman-Klass Measure of Volatility**

(a) *Short horizon*

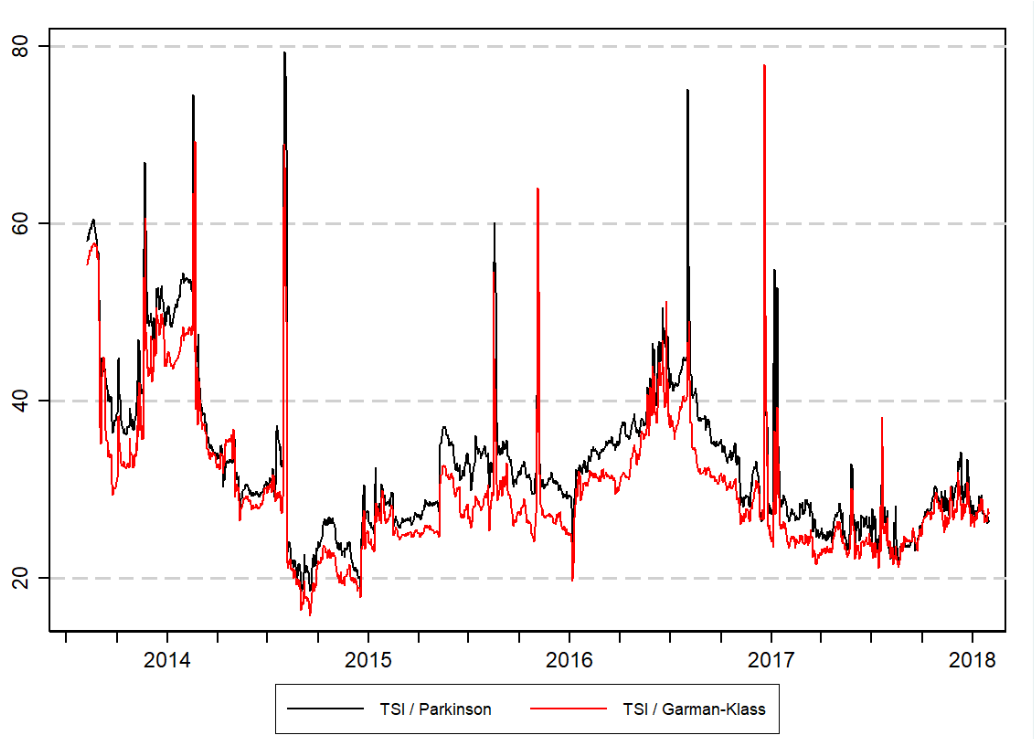
	BTC/USD	BTC/AUD	BTC/CAD	BTC/EUR	BTC/GBP	FROM others
BTC/USD	38.93	0.40	0.05	3.84	0.12	4.41
BTC/AUD	0.13	25.61	0.29	0.22	0.11	0.75
BTC/CAD	0.08	0.36	45.95	0.36	0.11	0.91
BTC/EUR	2.54	0.38	0.13	27.37	0.23	3.28
BTC/GBP	0.19	0.24	0.13	0.35	57.94	0.91
TO others	2.94	1.38	0.6	4.77	0.57	*TSI: 10.26/206 = 4.99%*

(b) *Long horizon*

	BTC/USD	BTC/AUD	BTC/CAD	BTC/EUR	BTC/GBP	FROM others
BTC/USD	42.32	3.59	0.34	9.77	0.62	14.32
BTC/AUD	3.28	60.34	3.22	6.21	0.61	13.32
BTC/CAD	0.17	4.83	45.66	1.17	1.31	7.48
BTC/EUR	14.71	3.69	0.54	49.11	1.29	20.23
BTC/GBP	0.39	1.32	1.20	0.62	37.61	3.53
TO others	18.55	13.43	5.3	17.77	3.83	*TSI: 58.88/293.92 = 20.04%*

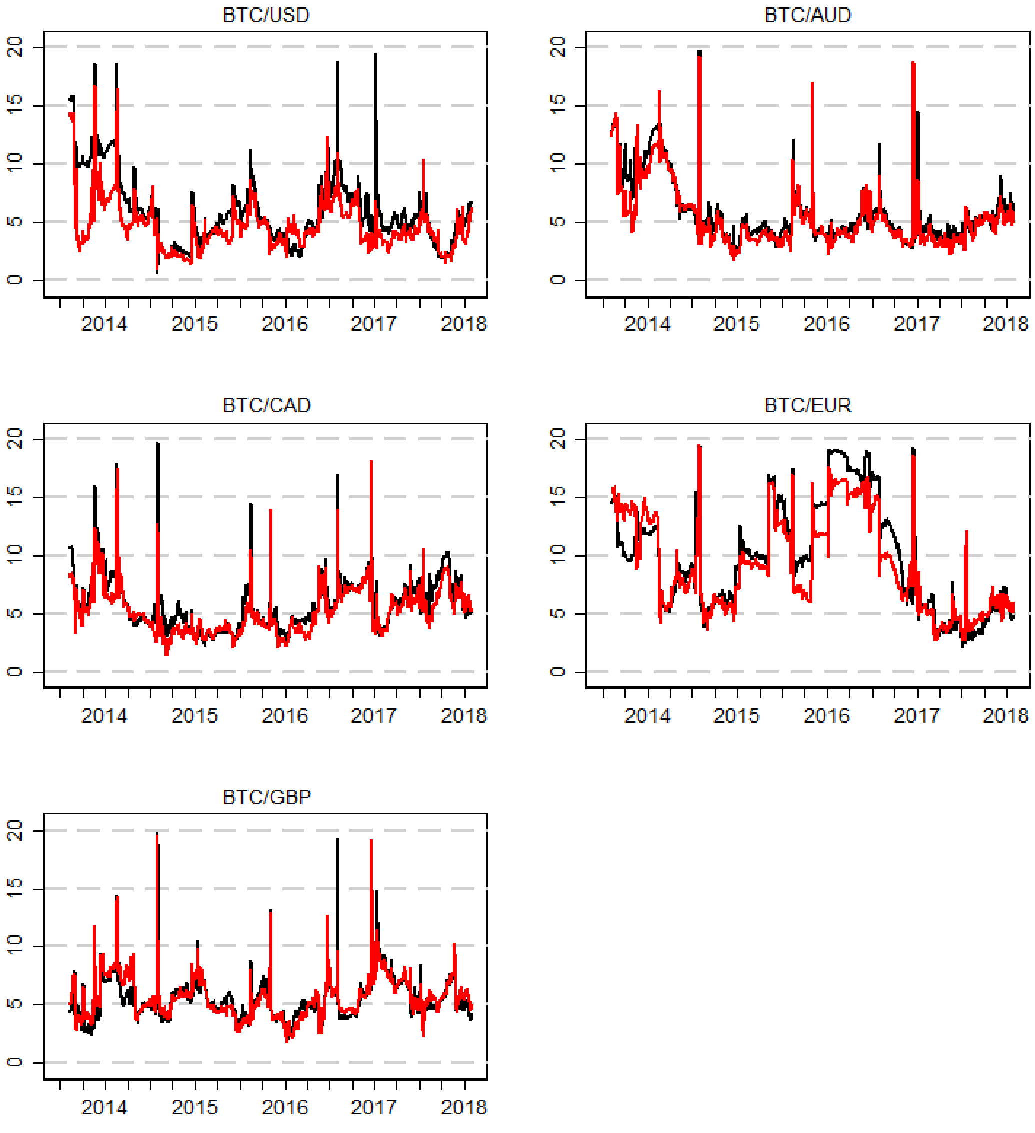
Note: Volatility spillovers, frequency domain analysis following Baruník and Křehlík (2018). Numbers are percentages. 'Within' refers to *within system* spillovers. *Short* and *Long* horizons refer to '4 days or less' and 'more than 4 days', respectively.

Figure 16 **Overall volatility spillovers (dynamic plot): Garman-Klass volatility measure**



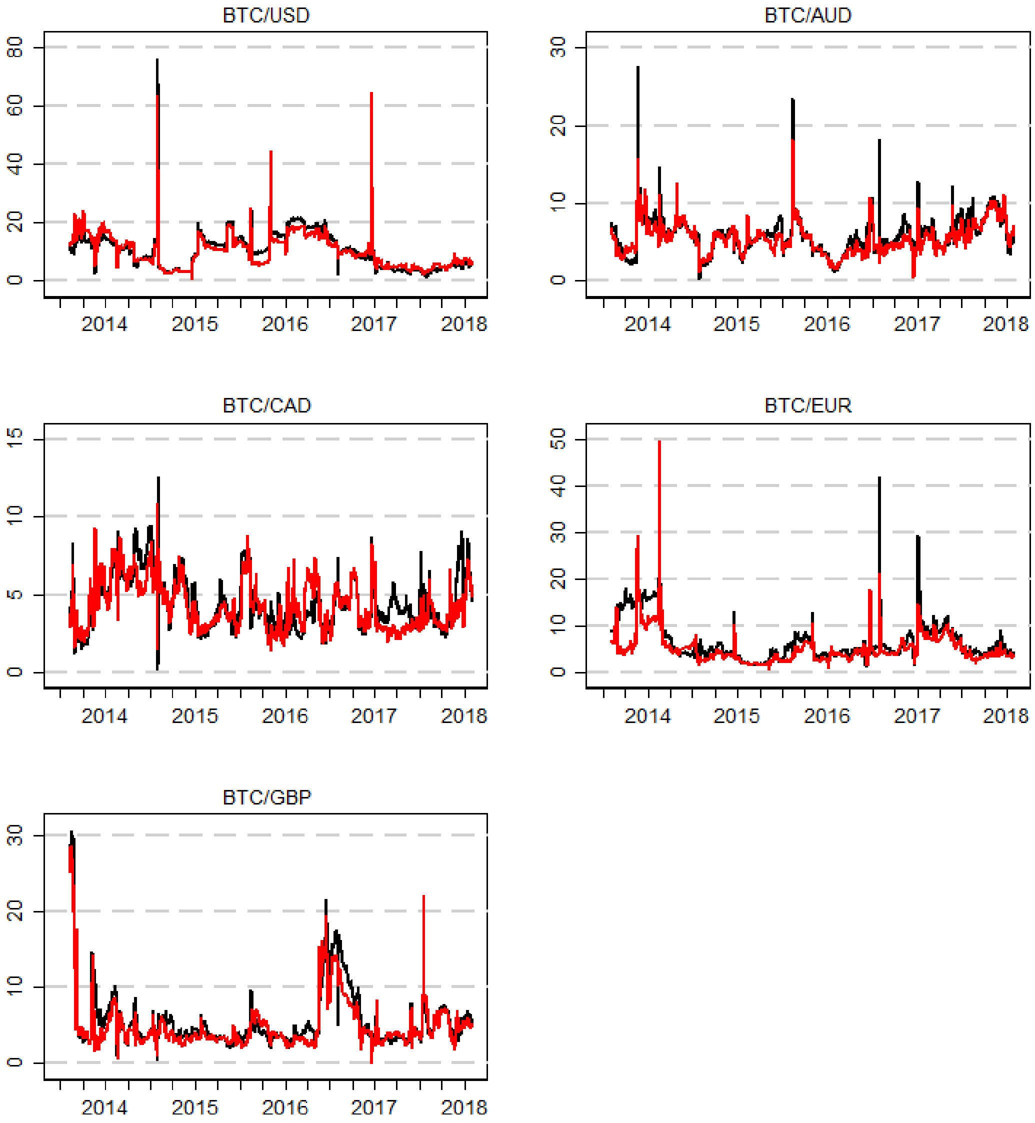
Note:The black line is the Dynamic overall based on Parkinson (1980) volatility, the red line is calculated based on GK-YZ (2002) volatility. Dynamic overall *volatility* spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window, Y-axis in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

Figure 17 **Volatility spillovers from others, dynamic plot: Garman-Klass volatility measure**



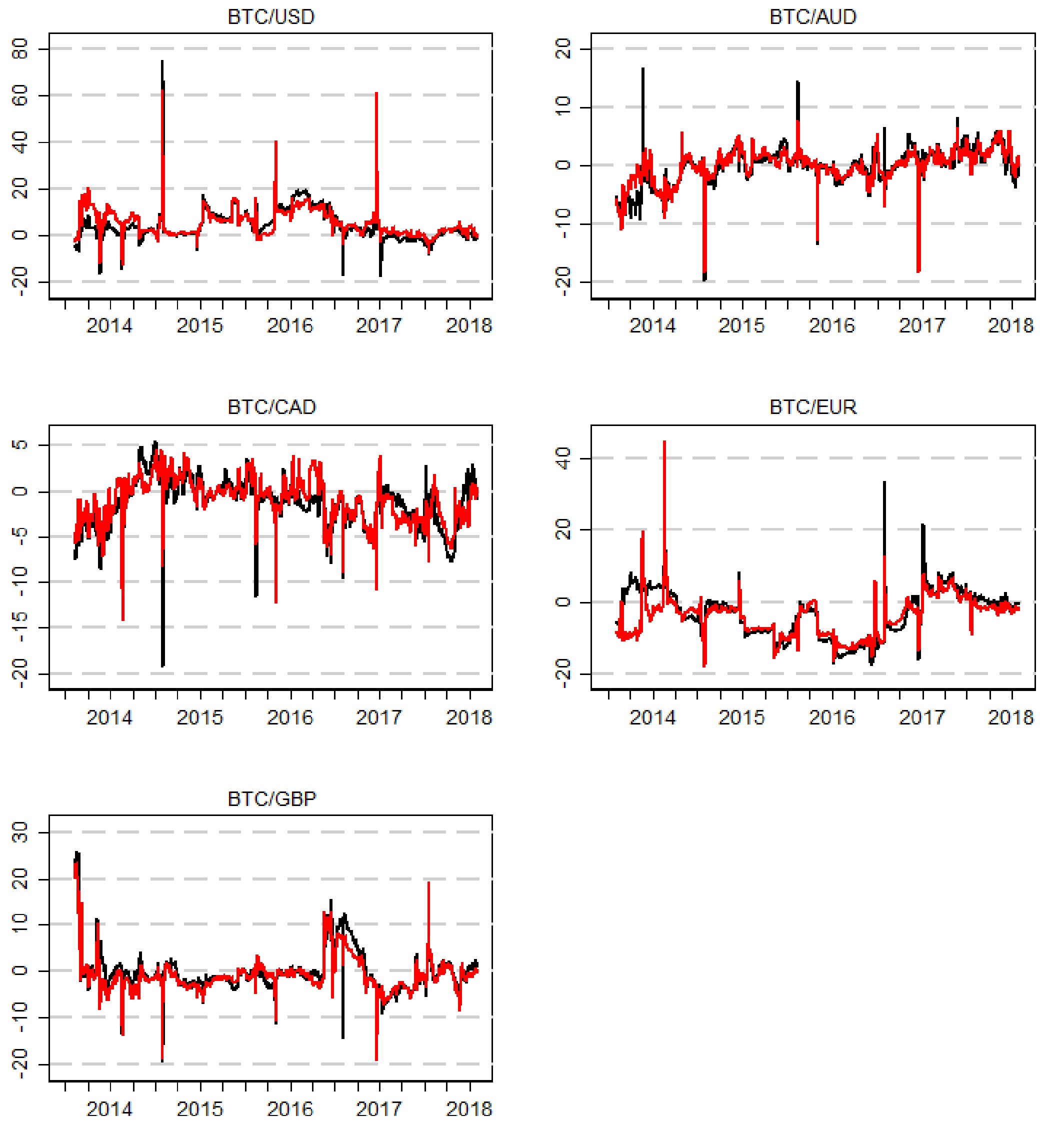
Note: Dynamic volatility spillovers *from* others computed following Diebold and Yilmaz (2012) with a 150-day rolling window. Y-scales in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

Figure 18 **Volatility spillovers to others, dynamic plot: Garman-Klass volatility measure**



Note: Dynamic volatility spillovers *to* others computed following Diebold and Yilmaz (2012) with a 150-day rolling window. Y-scales in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

Figure 19 **Net volatility spillovers, dynamic plot**



Note: Dynamic *net* volatility spillovers computed following Diebold and Yilmaz (2012) with a 150-day rolling window. Y-scales in percentages. Dates on the x-axis indicate the start of the year, and ticks are quarterly.

References

Alizadeh, S., Brandt, M. W., & Diebold, F. X. (2002). Range-based estimation of stochastic volatility models. *The Journal of Finance*, *57*(3), 1047–1091.

Alvarez-Ramirez, J., Rodriguez, E., & Ibarra-Valdez, C. (2018). Long-range correlations and asymmetry in the Bitcoin market. *Physica A: Statistical Mechanics and its Applications*, *492*(C), 948-955.

Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk*. *Journal of Financial Econometrics*, *16*(2), 271-296.

Bennett, C., & Gil, M. A. (2012). *Measuring historical volatility* (Tech. Rep.). Santander Global Banking: & Markets. (Equity Derivatives Division Technical Note)

Caporale, G. M., Gil-Alana, L., & Plastun, A. (2018). Persistence in the cryptocurrency market. *Research in International Business and Finance*.

Cheah, E.-T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? an empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, *130*, 32 - 36.

Cheah, E.-T., Mishra, T., Parhi, M., & Zhang, Z. (2018). Long memory interdependency and inefficiency in Bitcoin markets. *Economics Letters*, *167*, 18 - 25.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2018). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*. Retrieved from `http://www.sciencedirect.com/science/article/pii/S1057521918305271` doi: https://doi.org/10.1016/j.irfa.2018.09.003

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, *165*, 28 - 34.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366), 427–431.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158–171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57 - 66. (Special Section 1: The Predictability of Financial Markets Special Section 2: Credit Risk Modelling and Forecasting)

Fernández-Rodríguez, F., Gómez-Puig, M., & Sosvilla-Rivero, S. (2016). Using connectedness analysis to assess financial stress transmission in EMU sovereign bond market volatility. *Journal of International Financial Markets, Institutions and Money*, *43*, 126 - 145.

Gandal, N., Hamrick, J., Moore, T., & Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics*.

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *Journal of business*, 67–78.

Koop, G., Pesaran, M., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, *74*(1), 119 - 147.

Lucey, B. M., Larkin, C., & O'Connor, F. (2014). Gold markets around the world - who spills over what, to whom, when? *Applied Economics Letters*, *21*(13), 887-892.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *The Journal of Business*, *53*(1), 61–65.

Pesaran, H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*(1), 17 - 29.

Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335–346.

Rogers, L. C. G., & Satchell, S. E. (1991). Estimating variance from high, low and closing prices. *The Annals of Applied Probability*, 504–512.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, *148*, 80 - 82.

Wiggins, J. B. (1991). Empirical tests of the bias and efficiency of the extreme-value variance estimator for common stocks. *Journal of Business*, 417–432.

Yang, D., & Zhang, Q. (2000). Drift-independent volatility estimation based on high, low, open, and close prices. *The Journal of Business*, *73*(3), 477–492.

Yarovaya, L., Brzeszczyński, J., & Lau, C. K. M. (2016). Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. *International Review of Financial Analysis*, *43*, 96 - 114.